We thank the reviewer for the many useful comments. They have been incorporated into the revised draft, and we detail here how we have done so.

> Page 1267 line 7: The author has claimed that “The novelty of this work is designing optimization tool for the real time oil spill automatic detection using Entropy-Based Multi-objective Evolutionary Algorithm without involving NN or any image processing classiïňĄcation tools” but he has not provided any information regarding the real time implementation parameters like speed of the model or overall accuracy of the model for a reasonable dataset (not just one image).

The novelty of this work is designing best optimization tool based on Pareto optimal solutions for the real time oil spill automatic detection by comapring between Entropy-Based Multi-objective Evolutionary algorithm and non-dominated sorting genetic algorithm-II (NSGA-II) without involving others tool such as neural network or any image processing classification tools under wind speed conditions larger than 3 ms^{-1}. Indeed, the previous studies have executed artificial neural networks (Topouzelis et al., 2009; Mohanta and Sethi, 2012) or post-classification techniques (Barni et al., 1995; Calabresi et al., 1999), which are considered to be semi-automatic techniques (Marghany 2001). Furthermore, both artificial neural networks and post-classification techniques are time-consuming and the probability of misclassification does not always decrease as the number of features increases, especially when sample data are insufficient to investigate the spreading level of oil spill.

Then We added figures 8 and table 2 as follows:

Figure 8 illustrates the nondominated solution of different algorithms. From Figures 8 , it is clear that the solution of NSGA-II is much better than, Entropy, and E-MMGA. Further, Entropy solution is far from real Pareto front while, the solution of E-MMGA is gathered around the center of the Pareto front. Under this circumstance, E-MMGA tends to concentrate in one part of the Pareto front. On the other hand, NSGA-II maintained high degrees of diversity of their solutions during the searching of best optimal solution for either oil spill footprint detection or oil spill spreading level in COSMO-SkyMed satellite data. In this regard, the NSGA-II is able to better distribute its population along the obtained front than Entropy and E-MMGA.

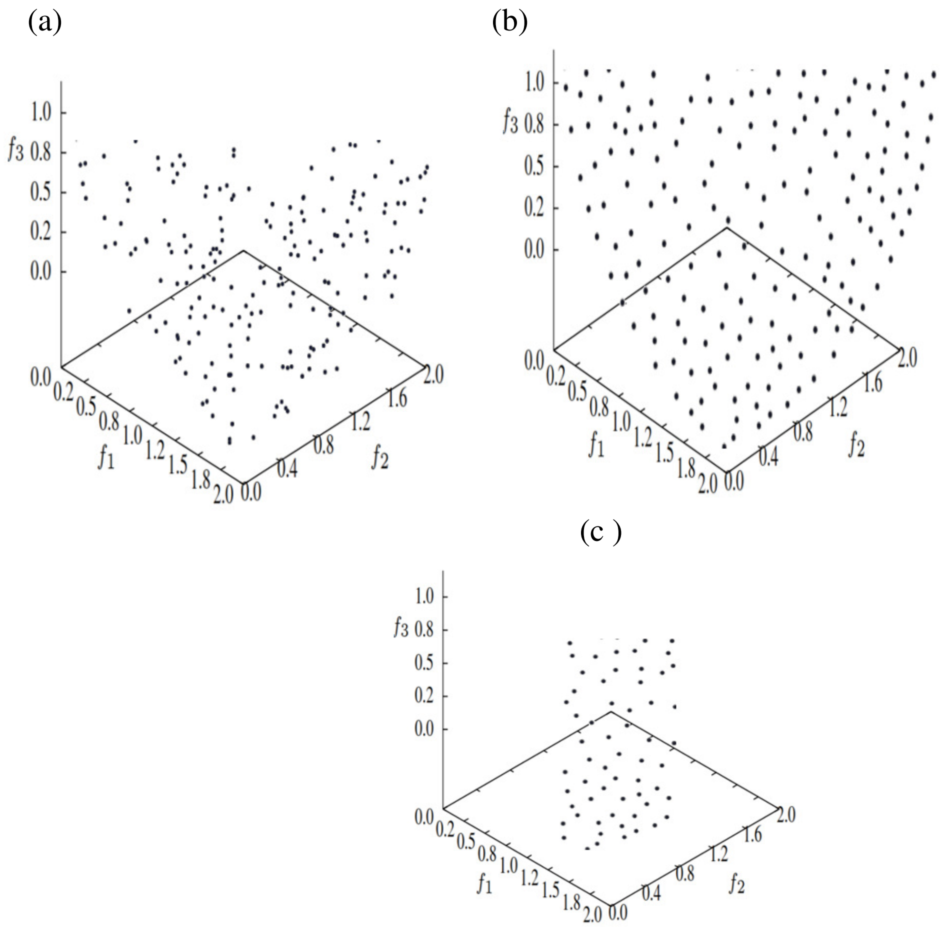

Figure 8. Final Nondominated solutions by using (a) E-MMGA, (b) NSGA-II and (c) Entropy

Then we added table 2 to compare between different algorithms and then add the following discussion too as follows:

This is mainly because each multi-objective function in NSGA-II tends to bias its population towards the extreme edges of the Pareto frontier. This is confirms the work was done by Deb et al., (2001). Compared to Entropy algorithm and E-MMGA, NSGA-II is able to identify the look-alike footprint boundaries and discriminate accurately between, oil spill and look-alike, and surrounding sea surface with standard error of 0.04 and fastest computing time of 65 sec (Table 2). NSGA-II can accurately identify the sharpest morphological boundary of oil spill and assigned by different segmentation layer in COSMO-SkyMed satellite data as compared to Entropy algorithm and E-MMGA. In fact, NSGA-II provides a set of compromised solutions called Pareto optimal solution since no single solution can optimize each of the objectives separately. The decision maker is provided with the set of Pareto optimal solutions in order to choose solution based on the decision maker's criteria. This sort of NSGA-II solution technique is called nondominanted since decision is taken after searching is finished.

Table 2. Accuracy performance of different algorithms

Algorithms	**Iterations**	**Time (sec)**	**Standard error**
Entropy	200	240	1.2
E-MMGA	700	140	0.89
NSGA-II	1200	65	0.04

3-

The result and discussion section is not convincing and it needs to be improved substantially. In fact it is not correct to discuss about the performance of a model in this filed just with several samples, on the other hand the comparison part of the study (with different state of the art models like NN or SVM) is missing.

We compared with other studies including NN and SVM as follows:

This confirms the work done by Deb (2000) and Deb et al., (2001). In this context, the Pareto-optimization approach does not require any a priori preference decisions between the conflicting of oil spill, look-alike, land, and surrounding sea footprint boundaries. Further, Pareto-optimal points have form Pareto-front as shown in Fig. 8 in the multi-objectives function of the COSMO-SkyMed data space. Finally, NGSA-II has advantages on Entropy and E-MMGA because (i) NGSA-II explicit diversity preservation mechanism;(ii) overall complexity of NSGA-II is at most $O(MN^2)$ and;(iii) elitism does not allow an already found Pareto optimal solution to be deleted. This agreed with Deb et al., (2001).

This study differs from the previous work performed by Marghany and Hashim (2011) because this work presents an automatic classification based on NSGA-II, whereas the study performed by Marghany and Hashim (2011) used an approach that is considered to be a semi-automatic tool for oil spill detection. In contrast to the previous studies of Fiscella et al. (2000) and Marghany and Mazlan (2011), the Mahalanobis classifier provides an oil spill classification pattern in which slight oil spill pixels can be distinguished from medium and heavy oil spill pixels. Nevertheless, the findings of this study are consistent with the results of Topouzelis et al. (2009). The NSGA-II algorithm was able to automatically extract oil spill pixels from the surrounding pixels without using a separate segmentation algorithm, as was done by Skrunes et al. (2012). Further, all the algorithms have been introduced are effectively depended on wind speed conditions. Nonetheless, the NSGA-II can automatically discriminate oil spill from the surrounding pixels even under wind speed of 6 ms^{-1}. Further, TCNNA algorithm of Garcia et al., (2013b) is based on entropy which first introduced by Marghany (2001) as excellent tool for oil spill detection in SAR data. Indeed, the capability of a SAR satellite to differentiate between oil, low wind areas, look-alikes is restrained by the noise floor of SAR. However, NGSA-II explicit diversity preservation mechanism is involved in NSGA-II is able to overcome this issue.
The Support Vector Machine (SVM) was implemented by Matkan et al., (2013) for automatic detection of oil spill is based on thresholding and is not able to provide any information regarding the level of oil spill footprint spatial variation from thickness to lightness levels as compared to NGSA-II.

Page 1264 line 19: “Synthetic aperture radar (SAR)” should be “Synthetic Aperture Radar (SAR)” throughout the manuscript you should use SAR.

It is corrected.

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