

# GENETIC ALGORITHM FOR SOUTH CHINA SEA WATER MASS VARIATIONS USING MODIS SATELLITE DATA

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**ABSTRACT:** This work utilizes the Genetic Algorithm (GA) for retrieving the water mass parameters from MODIS satellite data. In-situ measurements have contacted along coastal water of Malaysia on March 2014. The collected ground data of temperature and salinity are used to feed into Genetic Algorithm (GA) with selected MODIS satellite data. The challenge task is to optimize the errors have produced by existed algorithms of Sea Surface Temperature (SST) and Sea Surface Salinity (SSS). The new formula is developed based on optimization of genetic algorithm to retrieve sea surface density. The study shows that genetic algorithm can reduce the error of retrieving sea surface density with  $\pm 3.23 \text{ kg/m}^3$ . Further, coastal water Malaysia is dominated by water density of  $21.5 \text{ kg/m}^3$  which originally formatted in the Pacific Ocean. In conclusion, Genetic Algorithm (GA) can be used to retrieve water mass patterns using MODIS satellite data.

## 1. INTRODUCTION

Water masses are keystone to understand the dynamics of the ocean water circulation. Primarily, deep ocean circulation is energetic by minor modifications in seawater density which is triggered by differences in temperature and salinity, denoted as thermohaline circulation. Thermohaline circulation encompasses the formation and dynamic interchange of distinctive water masses. These are huge homogeneous volume of water which routes a distinctive variety of temperature and salinity. Utmost deep waters masses develop at high latitudes at the ocean surface wherever they attain their distinctive depleted temperature and salinity (Downes, et al., 2011). However, temperature is not ordinarily utilized to track a water mass since temperature gradually falls to the bottom and consequently reveals no extrema (maximum or minimum) rates like oxygen or even salinity. In fact, density differences between water masses is arising force that impels, water movements, usually vertical movements (Downes, et al., 2011). The flow of the major deep water gravity caused circulation pulling the denser water masses downwards, displacing lighter masses upward. In general, an oceanographic water mass is an identifiable body of water with a common formation history which has distinctive physical properties from surrounding waters. These include temperature, salinity, chemical - isotopic ratios, and other physical quantities (Marghany, M., 2012).

Up to now, Malaysian coastal water studies are reliant on classic field data observations without full understand to essential theories behind numerical modelling of coastal circulation. These activities are delivered similar pattern of coastal circulation as documented since Alejandro and Saadon (1996) and Alejandro and Demmler (1997). The novelty of ocean dynamic and water circulation on Malaysian coastal waters is absolutely vague. It well known that the monsoon winds are keystone of forming Malaysian coastal water physical properties and water dynamic movements in addition to tidal impacts (Wyrki 1961). Under these circumstances, the water temperature and salinity variations are function of monsoon winds fluctuations (Bowden 1983). Furthermore, in such shallow water of east coast of Malaysia which is less than 100 m water depth, tidal force can accelerate the water mixing processes through the water column (Marghany, 2009).

The MODIS (MODERate Resolution Imaging Spectroradiometers) on the *Terra* and *Aqua* satellites, both part of NASA's Earth Observing System, have each been providing high quality global sea-surface temperatures (SSTs) for over a decade. The importance of satellite SST measurements is clearly demonstrated by the succession of IR radiometers that have been operating since the launch of the first Advanced Very High Resolution Radiometer (AVHRR) in 1978. The AVHRR was followed by a spacecraft radiometer specifically designed for accurate SST measurement, the Along-Track Scanning Radiometer, ATSR. Methods used to derive SST in the infrared (IR) from space-based measurements of top of the atmosphere (TOA) brightness temperatures (BT) using dual or split

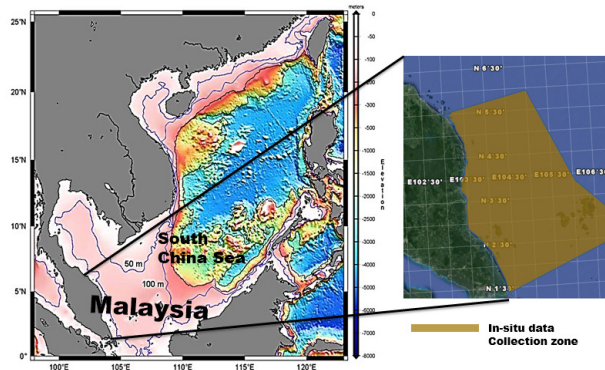
window algorithms are mature and the physical processes governing this measurement are well understood. Infrared (IR) satellite SST retrieval is based on measurements taken where the atmosphere is relatively transparent, in so-called “atmospheric windows” in the mid-wave infrared (MWIR,  $\lambda = 3.5\text{--}4.1 \mu\text{m}$ ) and long-wave, thermal infrared (LWIR,  $\lambda = 10\text{--}12 \mu\text{m}$ ) spectral intervals (Kilpatrick et al., 2015).

Sea surface salinity (SSS) retrieval from satellite data is a major challenge. Indeed, dissolved salts, suspended substances have a major impacts on the electromagnetic radiation attenuation outside the visible spectra range (Wong et al., 2007). In this context, the electromagnetic wavelength larger than 700 nm is increasingly absorbed whereas the wavelength less than 300 nm is scattered by non-absorbing particles such as zooplankton, suspended sediments and dissolved salts (Ellison et al., 1998). Therefore, Ahn et al., (2008) and Palacios et al., (2009) have derived SSS using colored dissolved organic matter, ( $a_{CDOM}$ ) from optical satellite data. Ahn et al., (2008) have developed robust and proper regional algorithms from large in-situ measurements of apparent and inherent optical properties (i.e. remote sensing reflectance,  $R_{rs}$ , and absorption coefficient of colored dissolved organic matter,  $a_{CDOM}$ ) to derive salinity using SeaWiFS images.

At present, there are three limitations to this remote-sensing technique (i) power constrains of the spacecraft permit only about two hours of scanning per day; (ii) cloud cover prevents observations; and (iii) light from near the sea surface (the upper 2 m) is sensed by the scanner. In this context, retrieving water masses based SST and SSS is not yet feasible, whereas is SST and SSS are suitable for direct observation with optical instruments. This work hypothesizes that water mass can be retrieved using optimization Genetic algorithm from MODIS satellite data. With this regard, Genetic Algorithm (Marghany and Mansor 2015) is considered to optimize the water mass which is based on SST and SSS for accurately synoptic measurements of water mass spatial variation in the East Coast of Peninsular Malaysia using Moderate Resolution Imaging Spectro- radiometer (MODIS).

## 2. STUDY AREA

The study area is situated in the east coast of Malaysia which is located on the eastern part of the Peninsular of Malaysia. As stated by Marghany [13], the coastal water is less than 187,71 nautical miles from shore and is quite shallow with the deepest area being about 60 m.



**Figure 1: Location of study area.**

The bottom has gentle slopes, gradually deepening towards the open sea. A clear feature of this area is the primary hydrologic communications between the estuary and the South China Sea which is the largest estuary along the Kuala Terengganu (Alejandro and Saadon 1996; Marghany 2009; Marghany 2012). Further, this area covers the zone of southern south China Sea and Sunda Shelf. In fact, east coast of Peninsular Malaysia borders the South China Sea is the largest water body in Southeast Asia which faces the continental shelf of Sunda platform, which has water depths not exceeding 100 m (Wyrki 1961). Air temperature is uniform throughout the year, varying from 24 °C to 28 °C with an average humidity of approximately 80%. The average amount of cloud covering over the sea 50 to 75% is also constant (Zelina et al., 2000). The northeast and southeast trade winds converge near the Equator.

## 3. DATA ACQUISITION

### 3.1 In Situ Data Collection

The study is conducted since 2002 to 2014 (Figure 1). However, the data collected on March 2014 are used due to limitation of the scope of this study. In doing so, more than 200 sampling locations are chosen (Figure 1). The

field cruises are conducted separately, area by area on the east coast of, Johor (March 2014), Peninsular Malaysia. In fact, it is major challenge to cover a large-scale area over than 700 k m<sup>2</sup> in short period using conventional techniques. Serial observations were made from water's surface to water depth of about 60 m.

The hydrolab equipment is used to acquire vertical water temperature and salinity profiles. Every field cruise has been conducted on 7 days in the east coast of Malaysia. Following Marghany (2009) and (Marghany 2012), the hydrolab instrument is lowered down from the sea surface to the sea bottom using winch. After it is lowered down to its sought depth, the information about temperature and salinity are collected digitally and then transfer to the computer through a cable which is connected from the hydrolab to computer. The record of digital reading is compelling every ten second with every 5 m water depth intervals (Marghany 2012).

### 3.2 MODIS Satellite Data

MODIS passively measures the reflected/emitted earth radiance at the top of the atmosphere at 36 different wavelengths. *Terra* MODIS has a daytime descending orbit with a 10:30 am local equatorial crossing time, whereas *Aqua* MODIS has a daytime ascending orbit and a 1:30 pm local equatorial crossing time. The MODIS sensors were designed for multi-disciplinary applications and research covering the atmosphere, land surfaces, the cryosphere and the oceans (Kilpatrick et al., 2015). The data are acquired on 12 March 2014.

### 3.3 Genetic Algorithm

The research methods are involved in situ measurement and implementing mathematical algorithms to retrieve water mass from Moderate-resolution Imaging Spectrometer (MODIS) i.e. the Aqua/MODIS data level IB reflectance satellite data. Then finally, genetic algorithm is validate using linear regression model and root mean square equation.

GAs optimization applications has many advantages. With this regard, GA advantages originate in algorithms itself, which imitate the mechanisms of the natural evolution, where a biological population evolves over generations to adapt to an environment by selection, crossover and mutation Marghany (2014a). In design optimization problems, fitness, individual and gens correspond to an objective function, design candidate and design variables, respectively. With this regards, the diversity of the population is maintained by a standard fitness sharing function. The best N selection is sued to determine the extreme Pareto solution. In doing so, the blended crossover is used to generate children on segment identified by two parents and specific parameter  $\ell$ . In this optimization, new design variables of water masses has a weight average as

$$Ch_1 = \varpi * P_1 + (1 - \varpi) * P_2 \quad (1)$$

$$Ch_2 = (1 - \varpi) * P_1 + \varpi * P_2 \quad (2)$$

where  $\varpi = (1 + 2\ell) * ran_1 - \ell$ ,  $Ch_1$  and  $Ch_2$  are child1,2,  $P_1$  and  $P_2$  are parent 1,2 which represent programmed scheme variables of the members of the new population and a reproduced pair of the old generation. Therefore,  $ran$  is random number which is uniform in [0,1].

Since the water mass  $\sigma_t$  is function of sea temperature (ST) and sea salinity (SS), its design parameters have to be addressed predictably. Else, the computation deviates and countless  $\sigma_t$  population cannot be weighed. Consequently,  $\ell$  is set to 0.0, then mutation takes place at a probability of 10%. When the mutation takes place, Eqs. 1 and 2 can be given as follows:

$$Ch_1 = \varpi * P_1 + (1 - \varpi) * P_2 + \alpha(ran_2 - 0.5) \quad (3)$$

$$Ch_2 = (1 - \varpi) * P_1 + \varpi * P_2 + \alpha(ran_2 - 0.5) \quad (4)$$

where  $ran_2$  is random number which is uniform in [0,1], and  $\alpha$  is set to 5% of the given range of each variable.

#### 3.3.1 The reproduction step

According to Sivanandam and Deepa (2008), Genetic algorithm is mainly a function of the reproducing step which involves the crossover and mutation processes on the  $\sigma_t$  population  $P_i^j$  in MODIS data. with this regard, the

crossover operator constructs the  $P_i^j$  to converge around solutions with high fitness. Thus, the closer the crossover probability is to 1 and the faster is the convergence (Sivanandam, and Deepa 2008). In crossover step the chromosomes interchange genes. A local fitness value effects each gene as

$$f(P_i^j) = |\sigma_i - P_i^j| \quad (5)$$

Then the crossfire between two individuals consists to keep all individual populations of the first parent which have a local fitness greater than the average local fitness  $f(P_{av}^j)$  and substitutes the remained genes by the corresponding ones from the second parent. Hence, the average local fitness is defined by:

$$f(P_{av}^j) = \frac{1}{K} \sum_{i=1}^K f(P_i^j) \quad (6)$$

Therefore, the mutation operator denotes the phenomena of extraordinary chance in the evolution process. Truly, some useful genetic information regarding the selected population could be lost during reproducing step. As a result, mutation operator introduces a new genetic information to the gene pool. The cross-over and mutation are described in brief in following sections which are subject to next step of Genetic Algorithm (Marghany 2014).

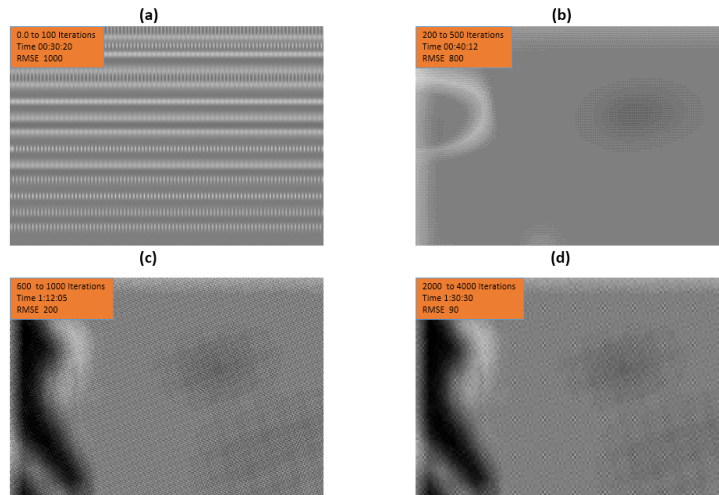
#### 4. RESULTS AND DISCUSSION

Due to heavy cloud covers during MODIS data acquisition on March 2014, the synoptic information of retrieved  $\sigma_i$  is not appropriately simulated (Figure 2). Most of the information about  $\sigma_i$  either onshore or offshore are completely fuzzy because of the heavy cloud covers during March. In fact, March represents the northeast monsoon which is dominated by heavy cloud covers. This confirms with work of Wyrтки (1961); Alejandro and Saadon (1996); Zelina et al., (2000) and Marghany (2012).



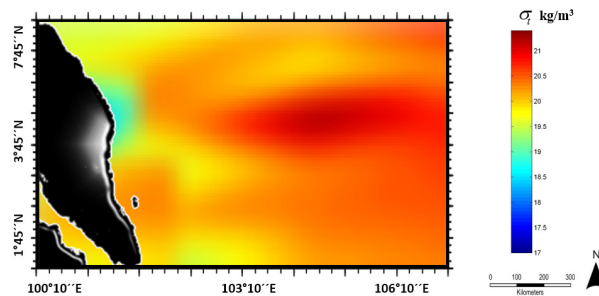
**Figure 2.**  $\sigma_i$  retrieved from MODIS data during March 2014.

Figure 3 shows the procedures of GA to retrieve  $\sigma_i$  from MODIS data. It is clear that GA reconstruct the information of land and sea surface fluctuation which are based on population generation step with different fitness values. Figure 3a shows the initial generation of  $\sigma_i$  with every 10 individuals. These individuals are encoded in binary values [0,1] as shown in brightness and dark pixels, respectively. It is interesting to find that with increment of iteration value of 4000, the fitness value is reduced with root mean square error (RMSE) of 90.



**Figure 3. Crossover procedures as a first individual with different iterations (a)100,(b)500,(c) 1000, and (d) 4000.**

Figure 4 shows  $\sigma_t$  retrieved from GA algorithm within 6000 iterations, RMSE value of  $\pm 3.23 \text{ kg/m}^3$ . Therefore, GA to produce synoptic  $\sigma_t$  map which is fluctuated from offshore to onshore. Onshore water density has lower value of  $18.5 \text{ kg/m}^3$  than offshore. However, the highest  $\sigma_t$  is occurred on offshore with maximum value of  $21.5 \text{ kg/m}^3$ . It is interesting to find that GA is able to retrieve the full scenario of  $\sigma_t$  fluctuation across the ocean compared to direct estimation from MODIS data (Figure 2). It means that GA able to generate a new population of  $\sigma_t$  although the existence of heavy cloud covers.



**Figure 4.  $\sigma_t$  retrieved from GA on March 2014.**

This because of the fact that Genetic algorithm is predominantly meaning of the reproducing which involves the crossover and mutation processes on the new population in MODIS data. In this aspect, the crossover operator creates the  $\sigma_t$  population to acquire optimization solutions based of high fitness. This confirms the work of Sivanandam and Deepa (2008) and Marghany 2013). On other words, Genetic Algorithm (GA) is capable of producing intricate  $\sigma_t$  patterns, and performing complicated computations. In addition, fitness function is selected to determine the similarity of each individual  $\sigma_t$  gradient changes in MODIS data even though of heavy cloud covers. This suggests that genetic algorithm is an excellent simulator of ocean water masses in optical data such as MODIS satellite data. This study confirms the capabilities of GA as simulating tool as reported by Kahlouche et al., (2002) and Sivanandam and Deepa (2008), Marghany (2013); Marghany (2015a); Marghany 2015b and Marghany (2016).

## 5. CONCLUSIONS

This study has proposed and demonstrated a new approach to retrieve water mass pattern from remote sensing data. The MODIS satellite data are acquired on March 2014. The real time physical water parameters such as salinity and temperature are collected during satellite over passed. Then, these data are used as input parameters for Genetic Algorithm (GA). Therefore, GA produced a new formula to retrieve water mass pattern by optimizing errors due to cloud covers, and SST and SSS linear algorithm implementations. The study shows that genetic

algorithm can reduce the error of retrieving sea surface density with  $\pm 3.23 \text{ kg/m}^3$ . Further, coastal water Malaysia is dominated by maximum offshore value of  $21.5 \text{ kg/m}^3$  which originally formatted in the Pacific Ocean. In conclusion, Genetic Algorithm can be used to retrieve water mass characteristics using MODIS satellite data.

## References

- Alejandro, C. and Saadon, M.N., 1996, "Dynamic behaviour of the upper layers of the South China Sea", Proceedings of the National Conference on Climate Change, 12-13 August 1996, Universiti Pertanian Malaysia, Serdang, pp. 135-140.
- Alejandro, C., and Demmler, M.I., 1997, "Wind-driven circulation of Peninsular Malaysia's eastern continental shelf", *Sci. Mar.*, 61 (2), pp. 203-211.
- Ahn, Y. H. P. Shanmugam, J. E. Moon, and J. H. Ryu (2008). Satellite remote sensing of a low-salinity water plume in the East China Sea. *Ann. Geophys.*, 26, 2019–2035.
- Amiruddin, A.M, Ibarhim, Z.Z., and Ismail S.A., 2011, "Water Mass Characteristics in the Strait of Malacca using Ocean Data View", *Research Journal of Env., Sci.* 5(1), pp. 49-58.
- Bowden, K. F., 1983, "Physical oceanography of coastal waters", Ellis Horwood Ltd. England.
- Downes, M.S., Anand, G., Stephen, M.G., and Jorge, L.S., 2011, "Water mass exchange in the Southern Ocean in coupled climate models", *J. of Phys. Ocean.*, 41, pp. 1756-1771.
- Ellison, W. A. Balana, G. Delbos, K. Lamkaouchi, L. Eymard, C. Guillou, and C. Prigent, 1998. New permittivity measurements of sea water. *Radio science*, 33, (3), pp. 639–648.
- Kilpatrick, K.A., Podestá, G., Walsh, S., Williams, E., Halliwell, V., Szczodrak, M., Brown, O.B., Minnett, P.J. and Evans, R., 2015. A decade of sea surface temperature from MODIS. *Remote Sensing of Environment*, 165, pp. 27-41.
- Kahlouche, S., K. Achour, and M. Benkhelif 2002, Proceedings of the 2002, WSEAS International Conferences, Cadiz, Spain, June 12-16, 2002.
- Marghany, M., 2009, "Linear algorithm for salinity distribution modelling from MODIS data", In proceedings of Geoscience and Remote Sensing Symposium, 2009 IEEE International, IGARSS 2009, 12-17 July 2009, Cape Town, South Africa, 3, pp. III-365 - III-368.
- Marghany, M., 2012, "Intermonsoon water mass characteristics along coastal waters off Kuala Terengganu, Malaysia", *Int. J. of Phys. Sci.*, 7(8), pp. 1294-1299.
- Marghany M., 2014a. Multi-Objective Evolutionary Algorithm for Oil Spill Detection from COSMO-SkeyMed Satellite. In Beniamino M., Sanjay Misra, Maurizio Carlini, Carmelo M. Torre, Hong-Quang Nguyen, David Taniar, Bernady O. Apduhan, and Osvaldo Gervasi (Eds.), ICCSA 2014. Part VI, pp 355-371.
- Marghany, M., 2014b. Utilization of a genetic algorithm for the automatic detection of oil spill from RADARSAT-2 SAR satellite data. *Marine pollution bulletin*, 89(1), pp. 20-29.
- Marghany, M., 2015a. Automatic detection of oil spills in the Gulf of Mexico from RADARSAT-2 SAR satellite data. *Environmental Earth Sciences*, 74(7), pp. 5935-5947.
- Marghany, M. 2015b, Genetic algorithm for three-dimensional ice floes from Tandem-X image. CD of 36th Asian Conference on Remote Sensing (ACRS 2015), Manila, Philippines, 24-28 October 2015.
- Marghany, M. and Mansor, S., 2015. Genetic algorithm for oil spill automatic detection using synthetic aperture radar. *Global Nest Journal*, 17(4), pp. 858-869.

Marghany, M., 2016. Automatic Detection of Oil Spill Disasters along Gulf of Mexico Using RADARSAT-2 SAR Data. *Journal of the Indian Society of Remote Sensing*, pp.1-9.

Sivanandam, S.N, and Deepa S.N, 2008, Introduction to Genetic Algorithms, by Springer Berlin Heidelberg New York.

Wong,M.,S., H., L.Kwan, J.,K. Young,Nichol,J., L., Zhangging,Emerson.N.,2007., Modelling of Suspendid Solids and Sea Surface Salinity in Hong Kong using Aqua/ MODIS Satellite Images. *Korean Journal of Remote Sensing*.Vol. 23 (3):161-169.

Wyrтки, K., 1961, "Physical oceanography of the South-East Asian waters" ., *In NAGA Report* Vol. 2, Univ. Calif Scripps Inst. Ocean., La Jolla.

Zelina, Z. I., Arshad, A., Lee, S.C., Japar, S.B., Law, A.T., Nik, M., & Marghany, M.M., 2000, "East Coast of Peninsular Malaysia". In: *Seas at The Millennium: An Environmental Evaluation*. Charles Sheppard (ed.). Elsevier Science LTD London, UK.