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Visualization of Ocean Colour and Temperature from Multi-Spectral Imagery Captured by the Japanese ADEOS Satellite

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***Abstract*:** The Ocean Colour and Temperature Scanner on board of the Japanese Advanced Earth Observing Satellite has been designed to provide frequent global measurements of marine chlorophyll levels and ocean temperature and created a means for visualizing the biological activity in the upper ocean. Over the time of its operation, the sensor captured the coverage of global oceans suitable for studies of the marine primary production and monitoring of fishery sites and environmental changes. Current radiative transfer techniques modelling marine chlorophyll levels based on optical reflectances captured by satellite sensors have to account for atmospheric path radiances superimposed onto the water-leaving radiance and a diversity of water suspended particles. Detailed modelling of geophysical processes and empirically constrained algorithms sometimes produce misclassifications. This paper presents chlorophyll concentration for several sites around the Pacific Ocean. Where the skill of the conventional chlorophyll algorithm is uncertain, the results given by an unsupervised neural network classification scheme are also provided. The hierarchical neural network introduced in the text extracts water pixels from images and reclassifies them to separate case 1 and case 2 waters and water radiances with the significant influence of the atmospheric attenuation.

***Keywords*:** OCTS, chlorophyll concentration, radiative transfer, neural network multi-spectral classification, Pacific Ocean.

1. Introduction

Global warming of the Earth and environmental changes are the devastating consequences of the continuing industrialization and population growth. The present state of the ocean is of special interest to a world concerned about the global climate change. Biological productivity of the ocean depends on chlorophyll which is the principal photosynthetic pigment of the plant kingdom in both terrestrial and marine environments (Jeffrey et al., 1997). The floating microscopic marine plant populations, known as phytoplankton, rely on chlorophyll to capture the energy of the sun and produce organic biomass. Phytoplankton are recognized as the basis of all biological production in the open sea supporting food webs and subsequently the world fisheries. Marine phytoplankton can influence chemical budgets and climate by a number of mechanisms. They utilize carbon dioxide from the atmosphere through photosynthesis affecting the carbon dioxide budget of the planet. With the sea occupying 70% of the Earth surface, the marine chlorophyll share in the global carbon dioxide uptake is the most significant. Phytoplankton blooms in upwelling areas, along continental shelf fronts, in coastal seas and estuaries have short generation times allowing chlorophyll to turn over 40 times a year (Hendry et al., 1987). Phytoplankton also make a contribution to the seasonal warming of ocean surface layers by absorbing and scattering light. Finally, they are responsible for the production of quantities of volatile compounds, such as dimethyl sulphide, which escape to the atmosphere and act as cloud-seeding nuclei.

Since the emergence of the first systematic Earth orbital observations in the 1960s, it has become possible to monitor environmental changes globally, instantaneously, frequently and in a consistent fashion. Satellites conduct homogeneous and regular measurements of atmospheric and surface parameters in regions with limited access which are too broad to allow convincing generalization of *in situ* observations, such as in the oceans, deserts and polar zones. The Earth is remotely scanned with a number of different sensors which design depends on a desired purpose of their mission. Following the pioneering investigations by Clarke et al. (1970) on the feasibility of deriving marine chlorophyll concentration from its influence on the spectral composition of light backscattered by the upper oceanic layers, a first especially devoted sensor, Coastal Zone Colour Scanner (CZCS), was launched in 1978. Eight years of the world ocean observation proved the capabilities of remote sensing techniques to monitor marine biomass and led to the definition of a new generation of ocean colour sensors supported by the Joint Global Ocean Flux Study. Parameters detectable from ocean colour sensors include chlorophyll concentration; diffuse attenuation coefficients of incident light in surface waters, suspended sediments and atmospheric properties, such as aerosol optical thickness and cloud characteristics. The Ocean Colour and Temperature Scanner (OCTS) has been designed as a successor to CZCS and launched in August 1996 on board the Japanese Advanced Earth Observing Satellite (ADEOS) (Kawamura et al., 1998).

Estimation and visualization of ocean properties and related atmospheric phenomena are of inestimable value for fishery industries, ocean physicists and biologists, climatologists, meteorologists and a number of other associated scientists. They are also most important for global change studies. This paper presents maps of marine phytoplankton for several sites around the Pacific Ocean based on the standard processing of OCTS imagery. Also described are the motivation and results of the ongoing research into the enhancement of satellite image interpretation using a neural network classification scheme.

2. Characteristics of the OCTS Sensor and Algorithms

2.1 OCTS Sensor

OCTS is an optical radiometer devoted to frequent global measurements of visible and infrared properties of the world oceans. It has 8 channels in the visible and near-infrared and 4 channels in the thermal-infrared ranges of the electromagnetic spectrum. The channels have been designed to provide a high radiometric sensitivity of readings suitable for the extraction of marine chlorophyll concentration (Oaku et al., 1997). Water-leaving radiances which are used to extract chlorophyll levels in most favourable conditions represent only 10% of the total radiance captured by a satellite (Antoine and Morel, 1997). The readings are dominated by the atmospheric path radiance originating from photons scattered by air molecules and/or aerosols which can also be reflected at the sea surface never at all penetrating the ocean. Spectral characteristics of OCTS are given in Table 1. The signal to noise ratio (SNR) is expressed as the mean square noise divided by the saturation radiance. Noise equivalent differential temperature (NEΔT) is given for thermal channels.

Table 1. OCTS channel characteristics.

Band		wavelength (nm)	saturation radiance ($W/m^2/sr/\mu m$)	SNR
1	violet	402-422	145	450
2	dark blue	433-453	150	500
3	blue-green	480-500	130	500
4	green	510-530	120	500
5	yellow	555-575	90	500
6	dark red	660-680	60	500
7	near-infrared	745-785	40	500
8	near-infrared	845-885	20	450
			saturation level (K)	NEΔT (K)
9	thermal-infrared	3,550-3,880	320	0.15
10	thermal-infrared	8,250-8,800	320	0.15
11	thermal-infrared	10,300-11,400	320	0.15
12	thermal-infrared	11,400-12,700	320	0.20

The spatial resolution of OCTS is about 700m at nadir viewing. Each scanning line covers approximately 1400km on the ground enabling the sensor to observe the same area every 3 days. The sensor tilts its line of sight along the track to prevent sunglitter at the sea surface from corrupting the transmission. For high sensitivity, each scanned pixel of every channel is represented by 10 bit digital count values.

2.2 Standard Algorithms for Ocean Colour and Temperature Extraction

In order to extract geophysical properties of the ocean, OCTS imagery has to undergo a thorough processing. Raw digital counts need to be time referenced and annotated with ancillary information, radiometrically and geometrically corrected, and geolocated. Then, specialized algorithms can be applied.

Current chlorophyll extraction algorithms are based on several assumptions. Radiative transfer models are built which apply the Lambertian postulate on natural surfaces (Elachi, 1987) and consider radiances coming from different origins to be separable (Smith and Baker, 1978). Image atmospheric correction is firstly performed. Under the assumption of separability of radiances, molecular (Rayleigh), gas, aerosol, and ocean radiances are isolated and individually modelled (Fukushima et al., 1998). Radiances originating from air molecular scattering are readily isolated knowing illumination and observation conditions, atmospheric pressure and wind speed at the sea surface. The central problem of atmospheric correction lies in the estimation of radiances due to aerosol and gas scattering since vertical and horizontal distributions of their particles cannot be established. Several models of atmospheric aerosols and gases are normally defined. Near-infrared radiances measured over pure oceanic waters and waters entirely dominated by phytoplankton and their by-products, called case 1 waters, are assumed to be fully dependent on the atmosphere. It is also often assumed that case 1 water leaving radiance in the red visible range of the electromagnetic spectrum is negligible. These wavelengths are therefore used to extract aerosol properties and extrapolate them towards the visible spectra (Antoine and Morel, 1997). Consequently, uncorrupted water-leaving radiances are calculated for the following investigations of ocean geophysical characteristics. The skill of the algorithms relies heavily on the concept of zero case 1 water leaving radiance in the near-infrared. In case 2 waters, additionally contaminated by suspended sediments, dissolved organic matter and terrigenous particles, there is a significant water leaving radiance in both the visible and near-infrared. In case 2 waters regular atmospheric correction methods fail because the extrapolation of aerosol path radiance into visible bands results in distorted or even negative reflectances at visible wavelengths. It is most complicated to partition radiance at the top of the atmosphere into components due to aerosols and suspended particulate material (Aiken and Moore, 1997). Therefore, approaches alternative to radiative transfer models are worth investigating.

The atmospheric correction algorithm routinely put to use at the National Space Development Agency of Japan (NASDA) considers all waters to be case 1 waters (NASDA, 1997). The land is concealed according to area maps and clouds are masked using thermal bands and the 8th near-infrared channel. An ocean chlorophyll concentration (OCC) equation has been derived empirically and the initial values of the coefficients have been adjusted to suit the sea around Japan (Kishino et al., 1998). The equation applies information coming from three channels and reads as follows:

$$\mathrm{OCC} = 0.2818 * \left[\frac{L_4 + L_5}{L_3} \right]^{3.497},$$

giving the amount of chlorophyll expressed in mg per m^3, and applying L_n, atmospherically corrected normalized water leaving radiances for the nth channel where L_3 is the blue-green, L_4 the green, and L_5 the yellow channel. Due to assumptions made by the atmospheric correction, standard OCC products occasionally produce a considerable misinterpretation of chlorophyll levels in areas with an intensified atmospheric attenuation, such as around cloud edges, high phytoplankton concentration, and over case 2 waters.

The sea surface temperature (SST) for OCTS imagery is calculated using the split-window method (Sakaida et al., 1998). It is a statistical algorithm applying the following regression equation:

$$SST = c_0 + c_1 T_{11} + c_2(T_{11} - T_{12}) + c_3(T_{11} - T_{10}) + c_4(T_{11} - T_{12})(1/\cos\theta - 1) + c_5(T_{11} - T_{10})(1/\cos\theta - 1),$$

where c_i are coefficients, T_n are brightness temperatures derived from level 1B brightness radiances for the nth channel, and θ is a viewing angle of the satellite.

Intensive efforts have been made to improve the quality of OCTS products (Kawamura et al., 1998). After the launch of ADEOS a field experiment called "Sanriku Campaign" was conducted during which a lot of sea-truth data was collected for the algorithm calibration and validation. Standard OCTS products have been by now revised several times. The current status of OCTS algorithms and some of the outcome of the mission have been described in a specially devoted issue of Journal of Oceanography, vol. 54, 1998.

2.3 Neural Network Extraction of Ocean Colour

In order to address the problems encountered by the radiative transfer models when dealing with globally distributed satellite imagery, the current research has introduced a multi-spectral image classification scheme (Ainsworth and Jones, 1999). The purpose is to find alternative methods of ocean colour extraction which could complement the existing models and together contribute to a better differentiation of upper ocean properties. As the aerosol correction is the most complex and vulnerable to errors, the classification algorithm exercises the whole vertical radiance column due to atmospheric aerosols and the ocean. The scheme is targeted to extract areas highly influenced by the atmosphere and segregate case 1 and case 2 waters based on spectral characteristics of brightness radiances uncorrected for aerosols.

Image brightness radiances are radio- and geometrically revised, geolocated, and corrected for the variable sun zenith angles and satellite viewing angles considering the absorption of the "standard atmosphere" ("standard aerosol" and Rayleigh scattering). All 12 channels of the OCTS can support the separation of water leaving radiance from radiances of land and clouds and contain important information regarding ocean colour and temperature. The proposed hierarchical algorithm uses eight visible and near-infrared and two thermal infrared channels to isolate water pixels from pixels of land and clouds. Subsequently, eight visible and near-infrared channels are applied to determine ocean reflectances dominated by the atmosphere and case 2 waters. Finally, only visible channels are used to extract a large variety of colour classes in case 1 waters. Water patterns are labelled based on experience with data set which means that the results could improve when a finer expertise of ocean colour is applied.

The pixel-by-pixel multi-spectral classification is performed. The scheme is fully unsupervised which means that no ground truth data are needed to perform the classification. The algorithm is based on the application of one of the artificial intelligence approaches, neural networks. Self-organizing feature maps have been put to use as the most appropriate neural network for the problem (Kohonen, 1987; Ainsworth and Jones, 1999). Figure 1 shows the topology of three-dimensional self-organizing feature maps which were used in these studies and their training and classification strategies. As far as the physical processing of satellite data is concerned, self-organizing feature maps essentially perform the least-square minimum difference clustering of radiance spectra defined by the OCTS multi-spectral pixel information (Iivarinen et al., 1995). Neural neighbourhoods assist the ordering of brightness radiances so that nearby neurons represent pattern classes with similar pixel spectral distribution. Neural weights approximate the brightness so that each neuron creates a multi-spectral generalization of the pattern class it portrays. On the more abstract level of cognition, self-organizing feature maps find an arbitrary large number of spectrum classes related to a variety of patterns on the Earth and within the Earth's atmosphere. Unlike radiative transfer models, neural networks make no assumptions on how spectra are distributed and interwound together. They discover purely natural divisions within data solely based on physical and chemical properties of the objects which the classes represent.

The entire reasoning leading to the neural network classification concept, self-organizing feature map architectures, and succeeding stages of the classifier are described in more detail in Ainsworth and Jones (1999). The conversion from spectra classes to phytoplankton concentrations is still not straightforward and other techniques will be proposed. The easiest would be the application of the standard OCC algorithm for extracted case 1 waters.

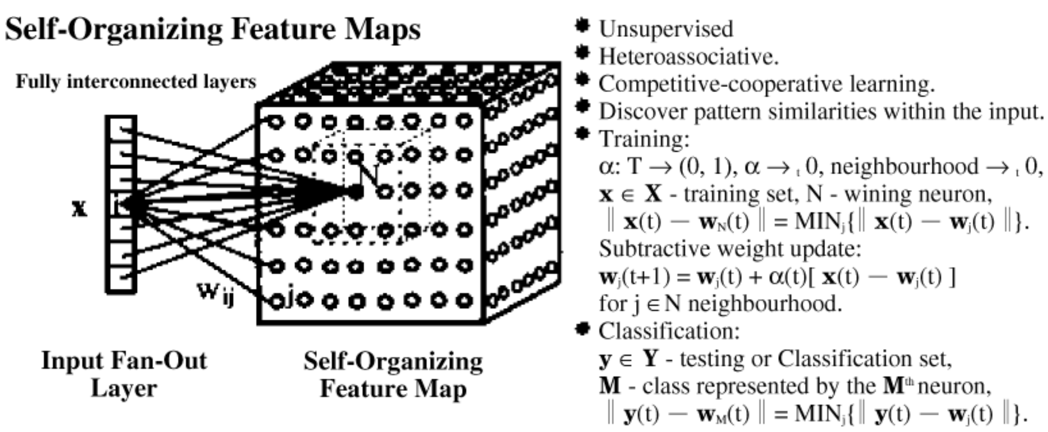

Fig. 1. Topology, learning and classification in self-organizing feature maps.

In the current paper, standard OCTS products will be compared to the outcome of the neural network analysis. Self-organizing feature-maps have been trained on combinations of six images out of a larger data set with scenes interlaced by lines to create a good data fusion and result generalization. A large number of ocean colour classes is allowed to be extracted, up to 729 classes. To display classified images, the three-dimensional neural configuration is mapped onto colours in the RGB colour cube allowing similar pattern classes associated with neighbouring neurons to be colour coded with similar colour shades. The presented standard OCTS products are in the Mercator projection while the classification results are in the satellite natural projection.

3. Standard and Experimental Chlorophyll Maps for the Pacific Ocean

OCTS imagery exposes many processes in the upper ocean (Jones and Ainsworth, 1998). The information includes mesoscale eddies, topographic upwelling, coral reef enrichment, coastal pollution, etc. Figure 2 shows the distribution of sites over the Pacific Ocean investigated in the current paper. The Figure represents monthly average global chlorophyll of the cloud free areas for April 1997. The primary production deserts in the centres of the North and South Pacific gyres can be clearly seen as well as high chlorophyll belts clustered along the coastlines where upwelling brings nutrient rich deep ocean water to the sunlit upper zone. Clouds and land are masked in black and the chlorophyll scale is given. The black section below Hawaii is the region where the scan angle of the sensor was routinely changed to prevent the sunglitter.

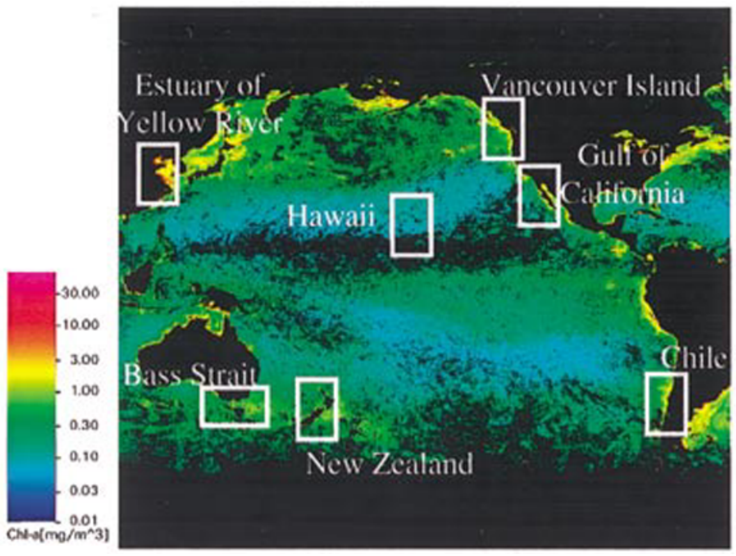

Fig. 2. Distribution of investigated sites over the Pacific Ocean, global OCC product for April 1997.

The standard chlorophyll concentration image for the island of Hawaii is presented in Fig. 3. Hawaii are volcanic islands located in the subtropical oligotrophic gyre with levels of chlorophyll below 0.2 mg/m^3. The islands are in the way of the warm westerly north equatorial current. Invariably warm waters and a steep continental slope with non existent coastal shelf do not create appropriate conditions to recycle the few nutrients washed into the sea. Red pixels in the open ocean adjacent to clouds are misclassifications and illustrate the sensitivity of the standard chlorophyll algorithm to atmospheric correction errors.

Figure 4 shows chlorophyll concentration in mid-spring along the western coast of Northern America centred on the Canada and U.S. border. The area is swept by two easterly currents, the cold subarctic current which after reaching the coast of America progresses up north to Alaska and the warm California current which flows down south towards the equator. Constant blowing of onshore winds induce coastal upwelling. High concentrations of chlorophyll can be seen west of the Vancouver Island and off Cape Blanco and Cape Mendocino. The intensification of the upwelling off the two Capes, where chlorophyll levels approach 3 mg/m^3, can be caused by a topographically induced mixing in the interior of the ocean (Lueck and Mudge, 1997).

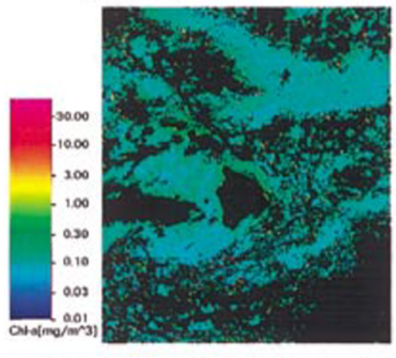

Fig. 3. Standard OCC product for the Islands of Hawaii, 5 May, 1997.

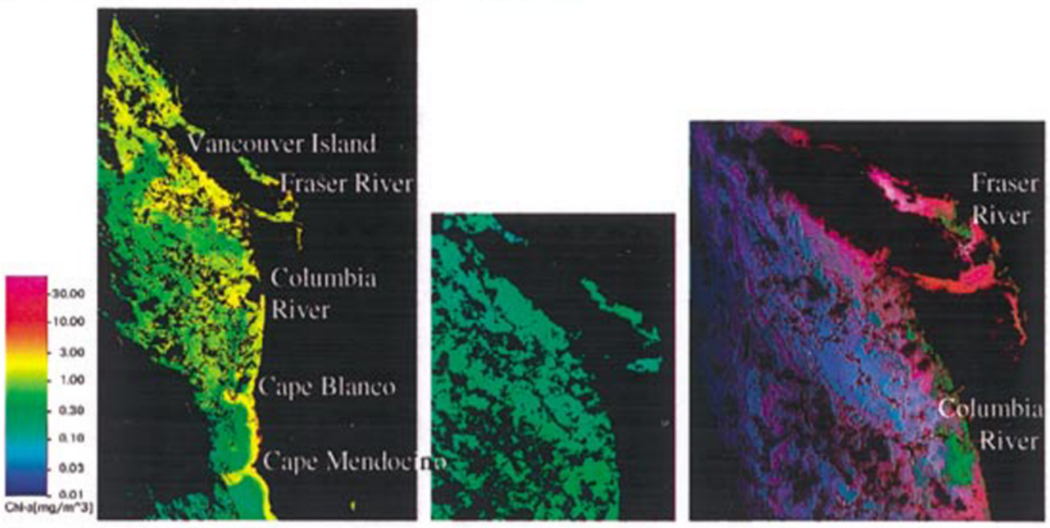

Fig. 4. Standard OCC product, left, standard SST product, center, and water pixel classification result, right, for the Vancouver Island Canada, 1 May, 1997.

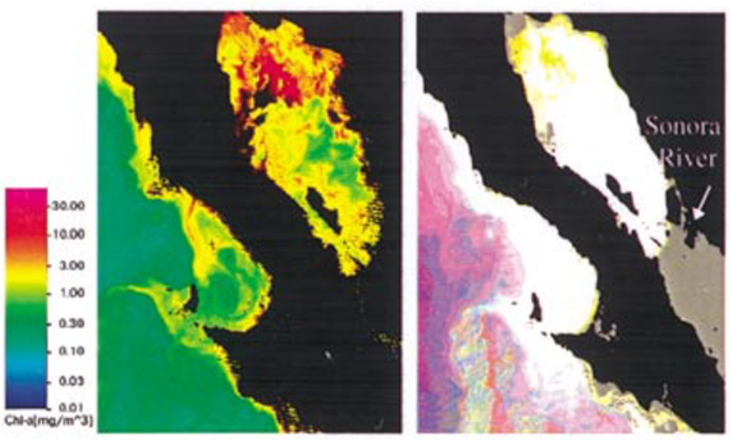

Fig. 5. Standard OCC product and case 1 water classification result for the Gulf of California, 19 March, 1997.

In the vicinity of the Vancouver Island there are estuaries of two rivers, Columbia and Fraser. The Columbia river drains a 671,000km^2 territory and transports agricultural nutrients to the sea. At the mouths of both rivers there are high productivity areas mixed with sediments, yellow substance, pollution, and debris, that is case 2 waters. The conventional algorithm, the left image in Fig. 4, has blanked out these waters due to negative values produced by the atmospheric correction. The SST product in Fig. 4 proves that there are no clouds covering the river outlets. The neural network classification of water pixels is able to extract a different colour of estuarial waters, shown in the image in green, and associate them with a specific case 2 water pattern.

The California current continues to flow towards the equator along the U.S. and Mexican shoreline. In the standard chlorophyll product shown in Fig. 5, current waters at the Gulf of California in Mexico appear almost blue because of the shortage of nutrients. Closer to land there is a higher pigment concentration. The winds on this coast are variable but in mid-March they are towards the equator inducing the Ekman transport. Warm water moving offshore is replaced by nutrient rich upwelled cold water from below the surface supporting high phytoplankton levels. Water blown away from the coast becomes depleted of nutrients and eventually forms part of the barren oceanic gyre. Some of the phytoplankton which at the end of their life sunk below the surface are remineralized to enrich the ocean floor.

The high level of phytoplankton at the head of the Gulf of California is a persistent phenomenon discussed by Santamaria-del-Angel et al. (1994). In the standard OCC product shown on the left in Fig. 5, the black regions surrounded by red in the Gulf are chlorophyll patterns which may have been confused by the atmospheric correction. The second image in the figure represents the neural network re-examination of case 1 water ocean colour with land and clouds masked in black and case 2 waters and areas with high atmospheric attenuation shown in grey. The research leading to the classification result shows that these waters are not case 2, neither influenced by a significant atmospheric attenuation. The neural network labelled them as almost white to the left of the faintly yellow streak corresponding to high phytoplankton concentration obtained by the conventional processing. The yellow streak of intensified chlorophyll represents waters with considerably high response from the red visible channel. The assumption of zero case 1 water-leaving radiance within the red spectral range can thus be questioned for validity. Gulf waters shown in grey very close to the north coast can convincingly be case 2 as implied by the neural approach but they were given high chlorophyll levels by the standard algorithm. There is also a clear water contamination in the bottom part of the gulf which was eliminated by both methods. The contamination is perhaps a pollution coming from the Sonora river.

The Chile coast is one of the world's strongest upwelling regions. The easterly circumpolar West Wind Drift while reaching the coast of South America progresses along the shore in a northerly direction as the Humbolt current. The prevailing winds have a consistent equatorial component throughout the year. All these conditions

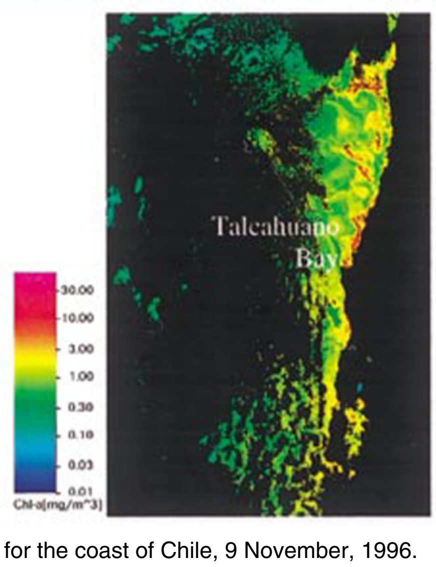

Fig. 6. Standard OCC product for the coast of Chile, 9 November, 1996.

lead to the persistent upwelling of cold nutrient rich waters clearly seen in Fig. 6. The matching SST maps show that cold water patterns correspond to the most productive areas. Previous studies found out that phytoplankton levels are high all year round in this region (Thomas et al., 1994). Filaments of chlorophyll rich waters are swept offshore in the more northerly part of the image. North of Talcahuano Bay chlorophyll concentration exceeds 10 mg/m^3. The intensified primary production supports a large fishery industry in Chile.

The highly productive Southern Ocean supports much marine life. Figure 7 shows that during summer in the southern hemisphere, the coastal ocean around the South Island of New Zealand is rich in phytoplankton. The area where the concentration of chlorophyll exceeds 1 mg/m^3 is over the continental shelf. The southern island is washed by the outer reaches of the easterly flowing cold circumpolar current. The western side of the island is also influenced by the distant fringes of the South Equatorial current which while reaching the north-eastern Australia progresses down south to the New Zealand coast. Shallow water and thermal structure of the ocean allow more nutrient to reach the sunlit region. Some fraction of the organic matter produced by phytoplankton sinks below the euphotic zone but storms and upwelling events make it available to support photosynthesis more readily than in the open ocean.

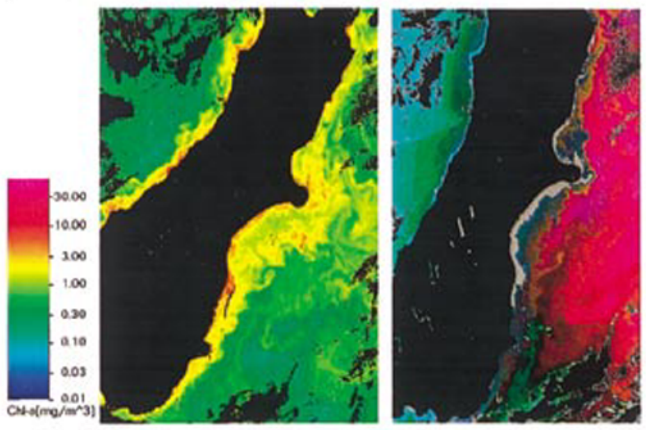

Fig. 7. Standard OCC product and case 1 water classification result for the southern island of New Zealand, 26 January, 1997.

The neural network classification has uncovered a variety of water types around New Zealand. The ocean on either side of the island differ. This is due to varying water constituents in the Tasman Sea and open Pacific. The classification result also indicates that some coastal waters on the eastern side of the island may likely be case 2, grey colour, for which the skill of the conventional chlorophyll algorithm cannot be trusted.

Bass Strait separates Victoria state in mainland Australia from the Tasmanian Island. Oceanic water in the Strait is shallow and clear. The area is secluded by the Australian and Tasmanian coasts and groups of islands on either side of Tasmania. Edges of circumpolar West Wind Drift waters get into the Strait but are unable to give rise to an intensified primary production what can be seen in Fig. 8. Consequently, chlorophyll levels in the Strait are around 0.3 mg/m^3. The conventional algorithm has obtained higher chlorophyll concentration in the Melbourne Bay, reaching 3 mg/m^3. The neural network classification has identified the Bay mainly being case 2 waters, grey

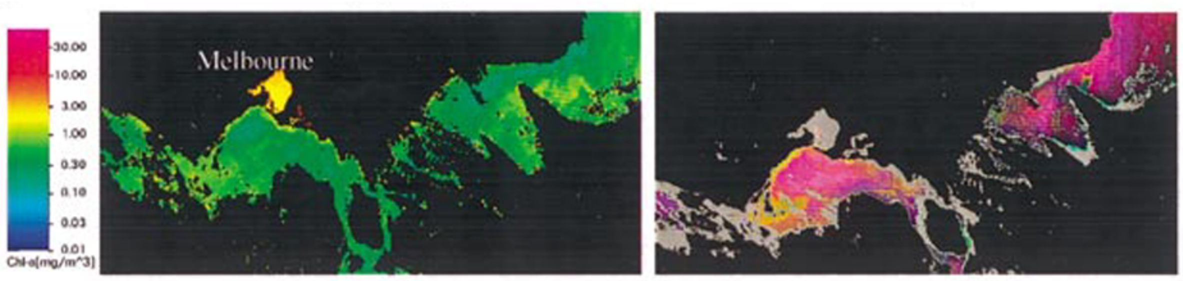

Fig. 8. Standard OCC product and case 1 water classification result for the Bass Strait, Australia, 27 November, 1996.

colour, which seems probable because of the surrounding Melbourne metropolis. Thus, the chlorophyll counts in the Melbourne Bay can be unreliable. The classification algorithm has also masked out in grey many near-cloud areas because of intensified atmospheric attenuation.

The Yellow River is the second largest river in China, running over 4,845km. It carries enormous amounts of yellow soil and sand which on average amount to 34kg/m^3 and maximally reach 580kg/m^3. It makes Yellow River the world's biggest as far as the outflow is concerned. The river flows into the Gulf of Chihli depositing soil at its estuary. It has been recognized that the entire Gulf of Chihli and waters around the Shantung Peninsula are engrossed with the circulated river outflow. The conventional algorithm of chlorophyll extraction, whose result is shown in Fig. 9, blanked out the whole of the Gulf of Chihli most likely due to negative water leaving radiances in the visible spectrum obtained by the atmospheric correction over waters with a high concentration of yellow soil. The traditional method has detected high phytoplankton levels in the water band surrounding the Shantung Peninsula. The waters around the Peninsula surely contain Yellow River sediments discharged from the Gulf of Chihli but in lower concentration than within the Gulf itself. These areas thus represent case 2 waters where conventional chlorophyll counts cannot be trusted. The neural network has objectively and uniformly classified the two water types as case 2, grey colour, providing a reliable background for following investigations of water constituents.

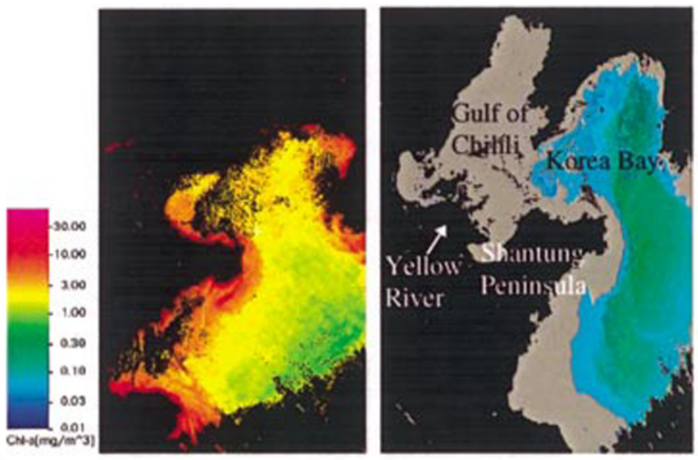

Fig. 9. Standard OCC product and case 1 water classification result for the Estuary of Yellow River, 2 November, 1996.

4. Discussion and Conclusions

With the sea occupying 70% of the surface of the Earth and providing an important component of mankind's protein, it is a resource that should to be used rationally. Chlorophyll with its role in primary production is an significant indicator of the health of the ocean and conditions leading to the global warming. It is important to monitor worldly phytoplankton levels and advance our understanding of oceanic processes. Chlorophyll concentration maps derived from satellite data show a variety of circumstances that create nutrient supply essential to phytoplankton growth. Some of these processes are offshore permanent upwelling, coastal recycling, and ocean nourishment by river outlets.

Standard radiative transfer models occasionally provide dubious results of chlorophyll estimation in areas with high atmospheric attenuation, e.g. around cloud edges, and in complex coastal situations, such as in case 2 waters. This paper has introduced a concept of hierarchical classification of satellite imagery which is initially corrected but still carries aerosol path radiance. The classification extracts water pixels and re-examines them to separate case 1 waters from case 2 waters and ocean reflectances relatively significantly affected by the atmosphere. The neural network algorithm has shown its skill in identifying ocean colours characterized by high near-infrared radiances where the expertise of conventional modelling cannot be fully trusted. It has also put in question the validity of the assumption of zero water-leaving radiance in the red visible spectrum in case 1 waters, especially for zones with elevated concentrations of chlorophyll. The neural approach has been able to monitor upper ocean processes and discover many regularities and phenomena unaccounted for by standard methods.

Future research will consider the analysis of case 2 waters which are very important in human everyday practice. The neural network scheme can complement the existing algorithms and contribute to the development of better products of chlorophyll monitoring throughout the globe.

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Author's Profile

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