Development of bio-physical model for the estimation of zooplankton biomass production in the Arabian Sea using remotely sensed oceanographic variables

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A bio-physical model was developed to estimate zooplankton production in the Arabian Sea using satellite derived chlorophyll concentration (CC) and sea surface temperature (SST). For this, US Joint Global Ocean Flux Study (US JGOFS) 1995 cruises in-situ data has been used. A 3D plot was generated using in-situ measured chlorophyll, temperature and zooplankton bio-mass. Scatter plot indicated linear and exponential relationship between CC - zooplankton biomass, temperature and zooplankton, respectively. A typical range of 24º-26º C water temperature was found preferable for zooplankton production. Based on this study a multiple regression analysis was carried out to derive coefficients for the development of algorithm. Correlation co-efficient ($r^2$) of multiple regression analysis was 0.78. An empirical algorithm was developed using these co-efficient. This algorithm was applied to Oceansat-1 derived chlorophyll concentration and NOAA-AVHRR derived SST to generate zooplankton images showing zooplankton biomass distribution and concentration. Model was validated through synchronous in-situ observations. Zooplankton biomass was measured on board Sagar Kanya and Sagar Sampda in the Arabian Sea. Regression analysis indicated co-relation co-efficient ($r^2$) = 0.74.

[Keywords: Biomass, Algorithm, Chlorophyll, Zooplankton, Biological forcing]

Introduction
Zooplankton encompasses an array of macro and microscopic animals. They feed on phytoplankton and facilitate the conversion of plant material into animal tissue and constitute the basic food for higher animals including their larvae. Distribution and abundance of zooplankton influence fisheries potential. Fishes mostly breed in areas where the planktonic organisms are abundant so that their larvae could get sufficient food for survival as well as growth. These phytoplankton-feeding copepods are the most important primary consumers in marine planktonic communities and, as such, form the base of all pelagic food chains. Zooplankton plays a key role in pelagic food chain by linking primary producers and secondary consumers. As food for the planktivorous fish and their larvae, zooplankton availability is considered to be one of the main factors determining commercial stocks. Availability of copepods is essential for the survival of larval stages of fishes which play an important role in recruitment process.

High concentration of zooplankton food stock may in turn allow certain small pelagic fishes to reach large population size. Zooplankton investigations in the Indian Ocean pertain mostly to taxonomy, zoogeography and ecology. These authors studied zooplankton standing stock through research vessel “Sagar Sampada” in-situ observations in the Arabian Sea. They found that shelf region was richer in zooplankton standing stock than the oceanic region. Highest standing stock value of 581ml/100m$^3$ was observed in coastal areas. Herbivorous dominated the zooplankton community and copepods were the most abundant i.e. 71.7%. Rao (1973) studied distribution of zooplanktons during the International Indian Ocean Expedition (IIOE). Dominance of copepods appeared to be nearly 70% of the total samples of zooplanktons. Copepods were the most important grazers in the ecosystem. Biological–physical interactions in the sea are characterized dynamics processes. These dynamic processes occur on multiple interactive scales.
Physical processes on an hourly time scale affect primarily the physiology of plankton, diurnal scales affect on growth rate and at longer scales affect on population as well as community dynamics. Thus, the rate of emergence of a particular physical event and its duration can strongly influence the bio-physical interactions in the sea are characterized dynamics processes. These dynamic processes occur on multiple interactive scales. The physical processes mass and size distribution of organisms. Large-scale interactions (such as changes in the global wind field) can influence small-scale interactions among predator and prey species. This affects the species composition and age structure of a food web. The understanding of the linkages among physical processes with biological processes and the transfer of produced organic matter through the marine food web involve several kinds of interactions. These interactions may be associated with exposure of phytoplankton cells to nutrients re-mineralized in the deep sea, exposure of phytoplankton cells to nutrients via heterotrophs in near-surface waters, the exposure of phytoplankton cells to light and predator–prey dynamics. A review of biological and physical interactions in the sea has been documented by McCarthy et al., (2002)\(^5\). Chlorophyll concentration and temperature can be used to explain the bio-physical processes. These two variables can be derived from satellite data. Satellites can provide synoptic and repetitive coverage data over large area, which is not possible through ship observation. Oceansat-1 with Ocean color monitor was launched in May 1999. Data of this sensor have been utilized operationally for nation wide fishery forecast\(^6\). Secondary production is the missing link of food chain in present potential fishing zones (PFZs) forecast technique in particular for carnivorous species exploration\(^7\). This modeling exercise investigates the link between physical and biological forcing and zooplankton production in the Arabian Sea as a first step towards an understanding of their effects on fish stock. Spatial distribution of prey fields is in marine systems controlled by physical and biological processes on various scales\(^5\). Coupled physical biological models can achieve a theoretical description of these complex processes. There has been some controversy over whether reproduction rate is regulated by temperature\(^8\) or by food availability\(^9\). There are number of field observations showing a linear relationship between chlorophyll and copepod egg production\(^10\), however this is not consistent, for example, Hay (1995)\(^11\) found no correlation between copepod production and chlorophyll in Northern Sea. Prestidge et al. (1995)\(^12\) computed the copepod egg production using in-situ surface temperature and chlorophyll concentration measurements. Relationship between the rate egg production and chlorophyll agree well with data observed. They observed that the copepods take most of their food at the surface.

**Materials and Methods**

*Analysis of US JGOFS 1995 In-situ data*

In this study we used Chlorophyll concentration, water temperature and zooplankton bio-mass data collected on board *R/V Thomas G. Thompson* ship in the Arabian Sea during January and March 1995 under US JGOFS 1995 programme. U.S. JGOFS data report was prepared by the U.S. JGOFS data management office at Woods Hole Oceanographic institution. Cruise tracks and sampling stations are shown in Fig. 1.

![Fig. 1](image)

*Fig. 1 – A map of Arabian Sea showing JGOFS cruise track during January and March 1995, (redrawn from US JGOFS data report edited by Cyndy Chandler, 2003).*

Months of January – March represents a massive bloom dinoflagellate *Noctiluca millaris* in the Northern Arabian Sea. Zooplankton data consist of micro-zooplankton species; they were sarscodine, tintinids, ciliates (non-loricate ciliate), copepods nauplii, etc. First the interrelationship between CC, water temperature and zooplankton bio-mass were studied. Three diamentioned scatter plots were generated to understand the inter-relationship between the variables (Fig. 2). A multiple regression analysis
was performed on zooplankton biomass as dependent variable and CC and water temperature as independent variable. The co-efficient derived from this regression analysis was used to develop model for zooplankton biomass estimation using satellite CC and SST estimates derived from IRS-OCM and NOAA-AVHRR, respectively.

Satellite data analysis

NOAA-AVHRR capture and analysis

Brightness temperature sensed at satellite height is influenced mainly by atmospheric moisture. Signal loss due to water vapor absorption is proportional to the difference brightness temperature in split channels of the thermal infrared. MCSST (Multi Channel Sea Surface Temperature) approach suggested by McClain et al. (1985) is being routinely used to compute SST from AVHRR thermal infrared channels i.e. Ch # 4 (10.3-11.3 μm) and Ch # 5 (11.5 - 12.5 μm). Processed products of SST were down loaded from NOAA web site at http://www.las.saa.noaa.gov/. SST images were filtered to remove the noise using a low pass filter. These satellite derived temperature were validated with in-situ SSTs during ship campaigns. Same day synchronous data were used for statistical analysis. A regression analysis was carried out using in-situ water temperature and satellite derived SST for all in-situ stations (Fig. 3).

OCM data analysis

The estimation of chlorophyll concentration from satellite sensor data includes a series of steps. The processing steps and procedure followed in the present study for digital data analysis of IRS P4 OCM to derived chlorophyll concentration been discussed by Chauhan et al., (2002). Atmospheric correction of OCM data was carried out using a method suggested by Gordon and Clark (1980). OC2 algorithm was applied to atmospherically corrected radiance for estimation of chlorophyll concentration. CC retrieval was validated with in-situ observation by Chauhan et al. (2002) in the Arabian Sea. CC and SST were different spatial resolution, i.e. 360 m and 1 Km, respectively. Chlorophyll concentration and SST images were brought to the same spatial resolution (1.0 Km) using an image-to-image registration technique.

Generation of Zooplankton-biomass images

The bio-physical model derived in the study was applied to remotely sensed data derived CC and SST to derive zooplankton-biomass images (Fig. 4). These images were colour coded showing the spatial distribution of zooplankton bio-mass. These images were used to generate validation data sets and comparison of spatial distribution of SST, chlorophyll and Zooplankton biomass in the study area.

Validation of model

In-situ measurements of zooplankton biomass were carried out in Arabian Sea to validate algorithm. For this, zooplankton measurements were carried out on board Sagar Sampda and Sagar Kanya. Zooplankton sampling was carried out using Multiple Plankton Net (MPN) and Bongo net. JGOFS protocol was adopted for measurement of zooplankton. Synchronous satellite data were procured for estimation of zooplankton using remote sensing in puts. Regression analysis was carried between measured and estimated data to understand co-relation.

Results and Discussion

Description of empirical bio-physical model
The modeling scheme adopted is largely driven by chlorophyll concentration and temperature. The approach is statistical (i.e. regression and derivatives) where an empirical relationship is used to predict the biomass directly from observed variables. This is potentially a viable alternative which could incorporate the benefit of using variables retrieved from satellite data as the forcing fields.

Fig. 2 shows 3D plot of oceanic variables measured during US-JGOFS 1995 cruise. The interrelationship between CC and zooplanktons indicates that there is a dependency of larval stages and adult zooplankton for food. It was observed that temperatures within 24-25°C range are preferred for zooplankton production. Chlorophyll is an indicator of food availability for zooplankton production. Majority of zooplankton draw most of their food at surface and subsurface. In this study the impact of water temperature is very well detected in the plot. In general, it is exponentially related but the optimum temperature range of 24-26 ºC was observed for high zooplankton biomass in the plot. This indicates that the water temperature play key role in controlling the production of zooplankton. It has become evident that both factors key plays role in controlling distribution of zooplankton biomass.

With this rationale, zooplankton biomass production in the model was empirically related to chlorophyll concentration and water temperature. A multiple regression analysis between zooplankton biomass and environmental variables (chlorophyll and water temperature) showed the important controlling factor in zooplankton biomass distribution. The correlation co-efficient \( r^2 \) was 0.78 in the analysis. The coefficient derived through this regression analysis were used to develop an empirical model in the following form.

\[
Z = \exp[7.71 + 0.88(\ln(chl)) - 0.189(SST)]
\]

Where \( Z = \) zooplankton biomass mgC.m\(^{-3}\), chl and SST are remotely sensed derived CC and sea surface temperature, respectively.

**Application of bio-physical algorithm for zooplankton biomass estimation**

The advantages in using satellite observations to derive the zooplankton biomass model are the broad spatial coverage and ability to incorporate seasonal and inter annual variability. CC is representative of the surface as well the water column of up to the euphotic depth. The surface temperature measurement is surface representation but less under stratified conditions as it will remain fairly representative of upper water column, where most cope pods are located. The major problems with ocean color satellite are inadequate accuracy in the coastal water due to high terrigenous load\(^{18}\) and removal of cloud contaminated pixels to ensure comprehensive coverage.

A model was applied to in-house generated chlorophyll images and down loaded SST images (SST validated through in-situ observation, \( r^2 = 0.87 \), Fig. 3). Fig. 4 shows chlorophyll, SST and zooplankton bio-mass images for the Northern Arabian Sea. It is observed from chlorophyll and SST that the two variables are inversely related. These waters are found to be having temperatures in the range 24-26 ºC and agree with the temperature preference reflected in Fig. 2. This indicates that the narrow range of temperature is effecting the zooplankton biomass production. Satellite derived chlorophyll provide indication of standing stock of biomass and have been used for exploration of fishery resources\(^6, 19, 20, 21\). Water temperatures have important biological implications on production and distribution of phytoplankton, zooplankton, fishes, and other organisms in the ocean. Application of satellite derived CC and SST for zooplankton estimation would be useful to understand availability of food resources for fish larvae.

**Validation of model**

Fig. 5 exhibits the scatter plot of is-situ measured vs. estimated zooplankton production using model. The estimated values using satellite derived CC and SST indicated well agreements with in-situ measured
values. Co-relations co-efficient ($r^2$) was observed to be 0.74. The bias observed may be due to (i) grazing of phytoplankton by zooplankton and (ii) difference in reproduction rate of phytoplankton and zooplankton. Grazing of phytoplankton reduces the chlorophyll concentration. This leads to under estimation of zooplankton in the model as zooplanktons are proportionally related to chlorophyll concentration. Phytoplankton life cycle is simple, it require 2-5 day for multiplication. The life cycle of zooplankton is comparatively lengthy consist of 4-5 larval stages, requires 1-2 week time for multiplication. The difference in multiplication rate of phytoplankton and zooplankton may some time leads to over estimations. These are the limitations of model. The strength of model is simplicity and easy to apply to remote sensing inputs. So estimation over larger spatial extent with high temporal resolution is possible in this technique which is a limitation in ship based measurements.

Conclusion
An empirical bio-physical model developed using US-JGOFS 1995 cruise in-situ data for zooplankton bio-mass estimation from remotely sensed chlorophyll concentration and Sea surface temperature. Model was run to generate zooplankton bio-mass images using remotely sensed derived CC and SST images. Zooplankton biomass indicated proportionally related with CC and exponentially with SST. Validation indicated well match between in-situ measure and model estimate. Regression analysis indicated correlation co-efficient ($r^2$) 0.74. The bias could be due to grazing of phytoplankton by zooplankton as well as the difference in multiplication rate of phytoplankton and zooplankton. Approach is useful for zooplankton biomass estimation and to understand the spatial distribution using RS data.

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References