RELATING THE DISTRIBUTION OF SOUTH AFRICAN PELAGIC FISH SPECIES TO ENVIRONMENTAL VARIABLES USING A NOVEL QUANTITATIVE APPROACH

Kobus J. Agenbag[1], Anthony J. Richardson[2], Herve Demarcq[3], Pierre Fréon[3], Frank A. Shillington[2] and Scarla J. Weeks[4]
[1]Marine and Coastal Management, Cape Town, South Africa
[2]Oceanography Department, University of Cape Town, South Africa
[3]IRD, FRANCE and MCM, Cape Town, South Africa
[4] Ocean Space CC and IDYLE associate, UCT, Cape Town, South Africa

The distribution of large pelagic fish (tuna and sword-fish) generally shows a positive relationship between abundance and sea surface temperature (SST) fronts. In the case of small pelagic clupeoids the situation is not so clear, with some studies on the distribution of Californian anchovy and South African sardine showing no relationship to SST, whilst those on North Sea herring and Chilean anchovy and sardine distributions finding concentration at fronts. These investigations, however, all used a correlative approach, which suffers from the problem of covariance between SST and other environmental variables not included in the analysis. This problem can be alleviated by constructing models that include a suite of pertinent environmental variables, so that the effect of each variable in the model is independent of the others.

We report here on recent research using an 11-year time series of satellite-derived SST images and commercial catch records of South African anchovy (*Engraulis capensis*), sardine (*Sardinops sagax*) and round herring (*Etrumeus whiteheadi*). The index of fish distribution used in the models was "catch-per-set" (the tonnage of fish caught in a single haul). Research conducted in other purse seine fisheries (*eg.* West Africa) has demonstrated a relationship between mean catch per set and population size. We extrapolate this idea by assuming that similar relationships also exist at intermediate spatial scales and hence that catch per set and reflects local abundance. The initial set of predictors consisted of 20 variables, including seven temporal and spatial variables, four variables related to the fishing boat's characteristics, four related to solar and lunar ephemera, and five SST-related variables. This number was empirically reduced to a set consisting of year, month, time of day, latitude, water column depth, length of boat, moon phase, moon angle, sea surface temperature (SST), an index of frontal intensity (standard deviation of SST), and an index of SST warming or cooling (temperature difference between successive SST images). Model building was a two-step process. First, we built generalized additive models (GAMs) for each species to identify relationships between distribution and environmental variables. From the functional forms suggested by the GAM analysis, we developed predictive equations by constructing general linear models (GLMs). GLM is a rigorous approach supported by considerable statistical theory that combines ANOVA (categorical) and regression (continuous) variables to yield a predictive equation. GAMs do not produce predictive equations but are particularly adept at identifying non-linear relationships between variables.

The process is demonstrated in Figures 1 and 2. The GAM model, for example, showed that the variable 'time' had little effect on sardine catches (Fig. 1) and was thus not included in the GLM model (Fig. 2) for this species. Also, note that the GAM model suggested that variable 'latitude' should be implemented as a linear relationship and that 'length' (the size of the fishing boat) is best represented as a quadratic function. In the final GLM models the environmental variables accounted for 42.5%, 25.2% and 39.8% of the variance in distribution (catch-per-set) of anchovy, sardine and round herring respectively.

We further found that the relative importance of the individual environmental predictors varied considerably amongst the three species. The influences of the SST variables were not very strong (Fig. 3) but indicated larger catches of sardine in warm water and in cool water for anchovy and round herring. We also show that the influence of the SST standard deviation is generally very low, at least at the spatial and temporal scales used in this study (one week and 15 kilometers respectively). We suggest that a model

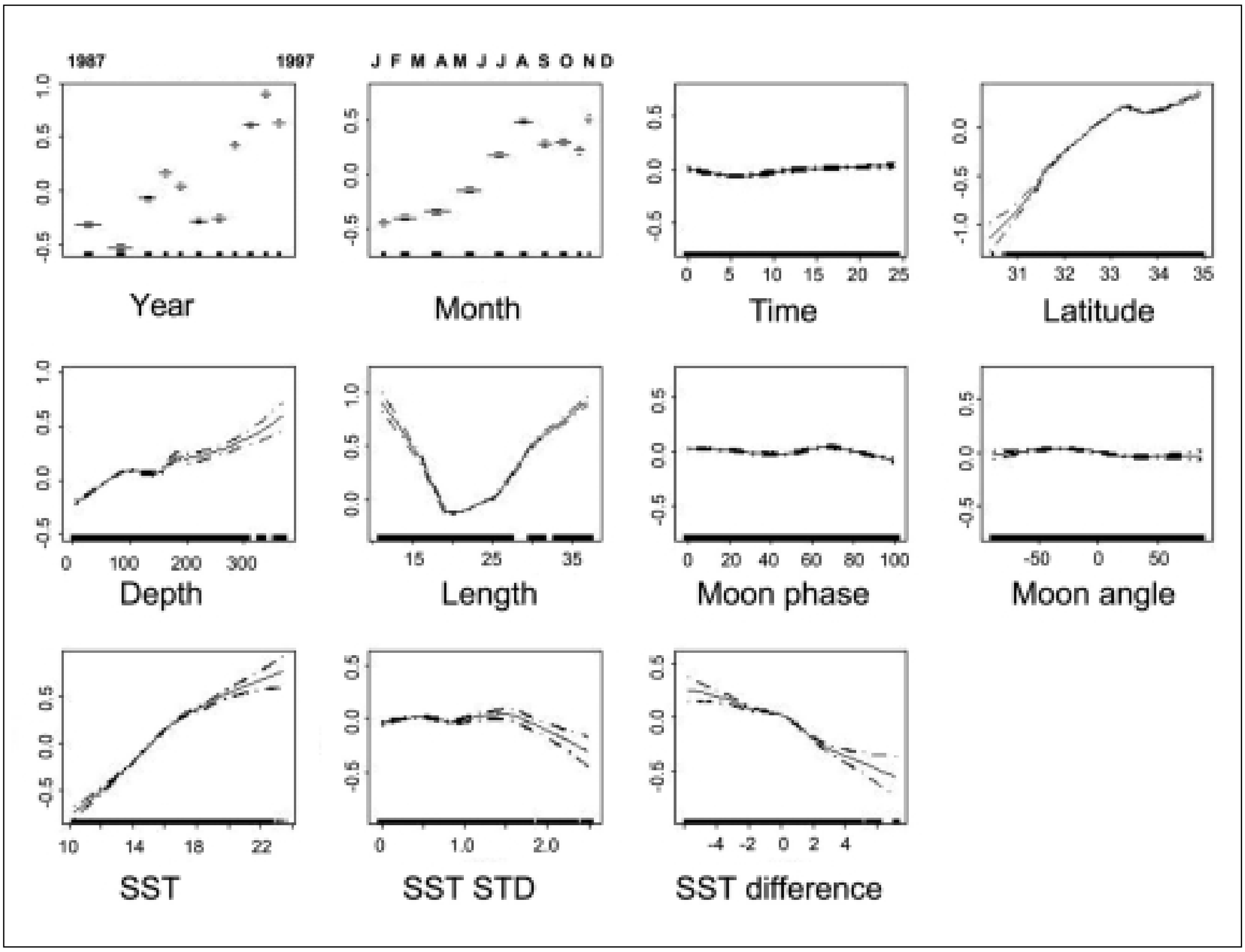
1987
1997
Year
J F M A M J J A S O N D
Month
Time
Latitude
Depth
Length
Moon phase
Moon angle
SST
SST STD
SST difference

Fig. 1

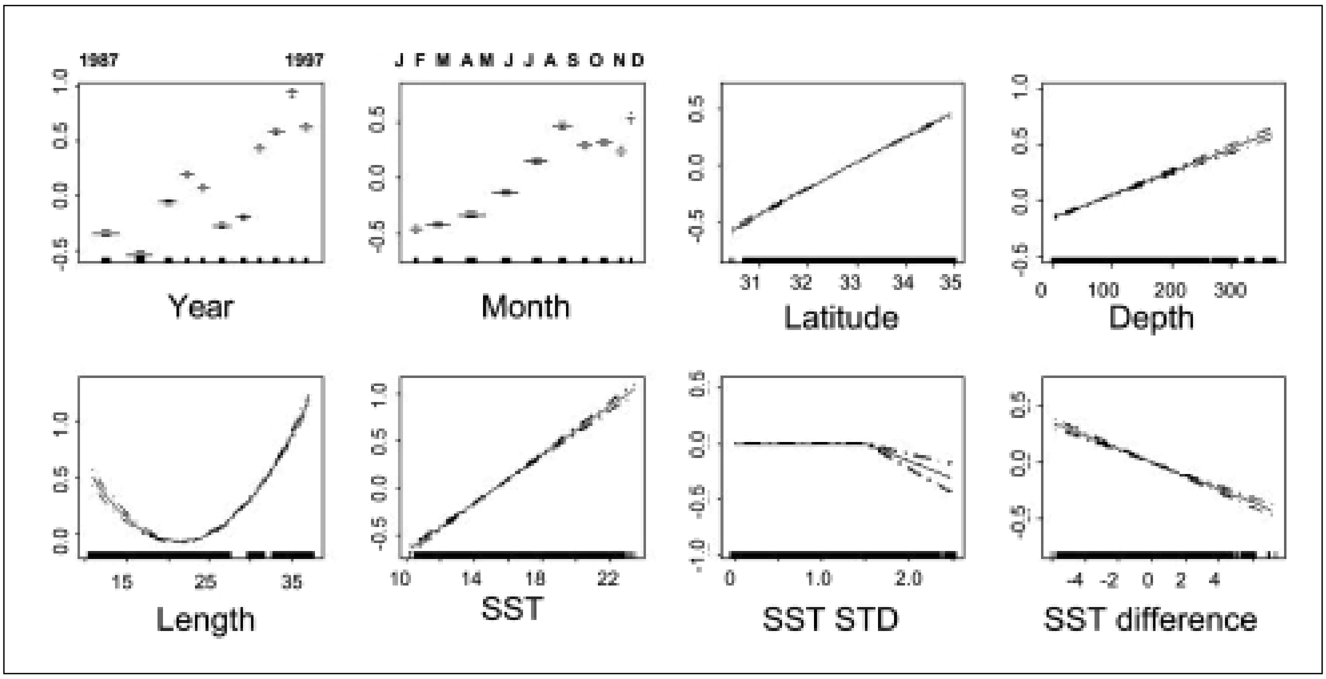
1987
1997
Year
J F M A M J J A S O N D
Month
Latitude
Depth
Length
SST
SST STD
SST difference

Fig. 2

building approach using GAMs and GLMs can be applied fruitfully to studies relating fish catches to environmental variables but it is also clear that to fully understand factors influencing pelagic fish catches, information on enrichment processes, species interaction and the fishing strategy of skippers need to be considered. It is further evident that the variable "catch-per-set", used by us to quantify fish distribution is very dependent on non-environmental variables (such as boat size) and also on fishing strategy. It would therefore be very desirable to find a more appropriate distribution index, or to construct a sub-set of the data in a manner that would eliminate such known problems.

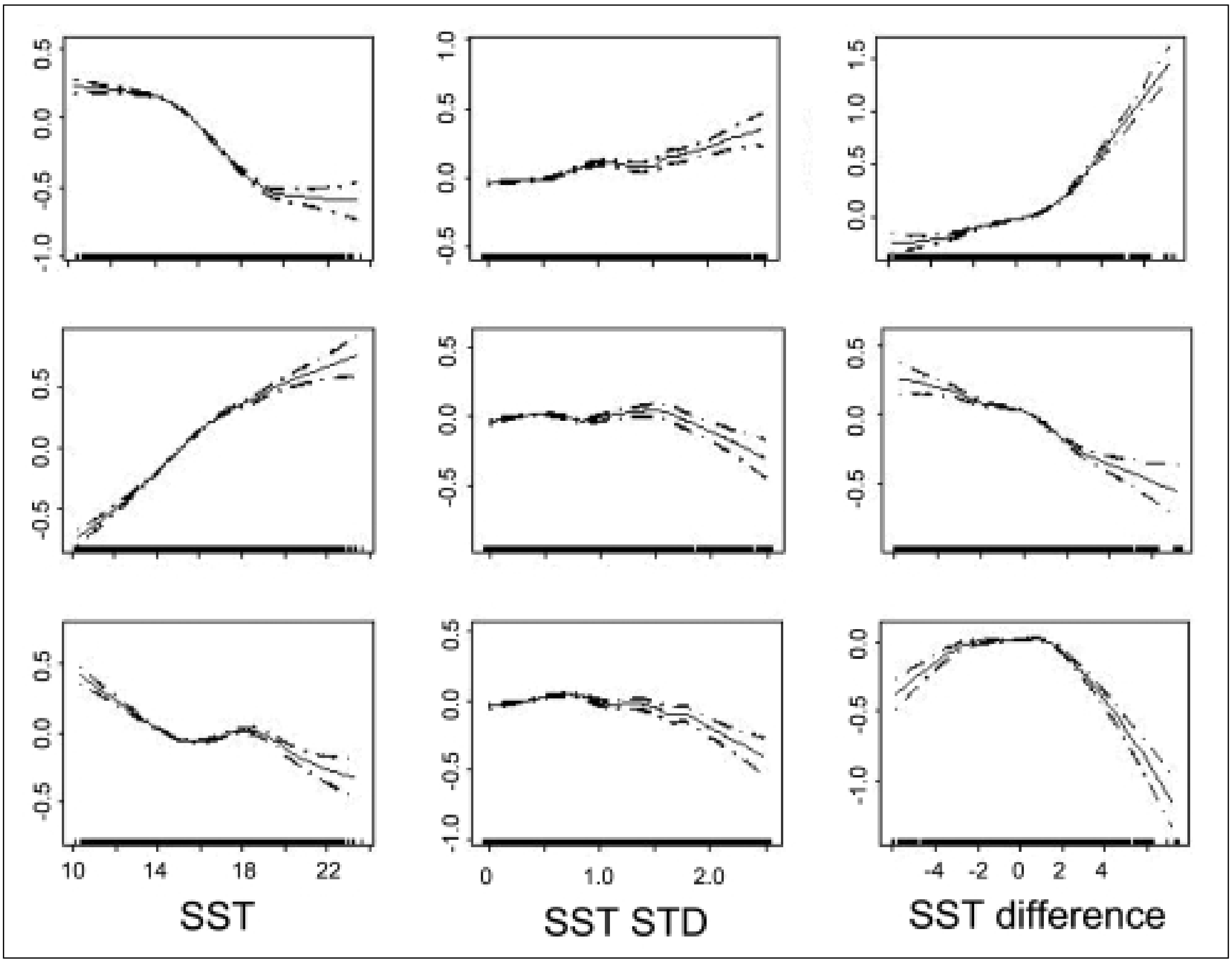

Fig. 3

Figure Legends

Figure 1. Sardine distribution ("catch-per-set") as a function of 11 predictors as obtained from a GAM model.

Figure 2. The functional forms of sardine distribution ("catch-per-set") versus eight predictors as deduced from Figure 1 for implementation in the GLM model.

Figure 3. Anchovy, sardine and round herring distribution as a function of SST variables after the effects of other variables have been removed by the GAM model.