

Data Fusion of Sea-Surface Temperature Data

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INTRODUCTION

The problem of data fusion, the merging of data taken by different sensors, becomes ever more relevant with the launch of each new remote-sensing platform. In a nutshell, the goal of data fusion is to combine the strengths of the various measurements to produce a dataset superior to that of any single instrument. As the number of sensing instruments grows, so do the opportunities for improved estimation

One example of considerable current interest in the climate-change community is the production of an improved sea-surface temperature (SST) map[2]. In particular, two state-of-the-art instruments - the Along Track Scanning Radiometer (ATSR) and AVHRR - share complementary features: ATSR allows excellent cloud discrimination and atmospheric correction based on its dual-view scanning geometry, but observes only narrow swaths of ocean; AVHRR suffers from low-wavenumber atmospheric distortions and cloud contamination, but has extensive global coverage.

In this paper we propose a methodology for combining ocean skin temperatures from the ATSR and AVHRR instruments to produce a continuous analysis at one-sixth degree spatial and three-day temporal resolutions, together with reliable error estimates, from the fusion of multiple datasets with arbitrary sampling characteristics, resulting in estimated temperatures which unite the precision of ATSR with the superior coverage afforded by AVHRR.

DATA FUSION

Data fusion is the product of three steps:

1. A prior model (e.g., a covariance or correlation structure) for the unknown field x of interest.
2. A determination of the model that relates the measurement y_i of satellite i with random field x .
3. An estimation algorithm, which solves a least-squares

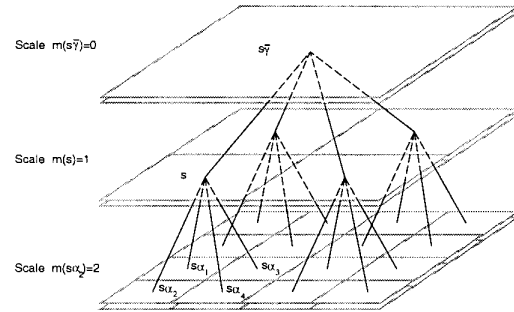


Figure 1: An example multiscale quad-tree for modeling *joint* 2D processes.

problem to determine the optimal estimates \hat{x} as a function of the measurements.

For our estimator we have chosen a multiscale or hierarchical method [4, 5], which has shown some promise in the estimation of remotely-sensed fields for a variety of prior models. Software for the estimator is available in the public domain¹, so for the purpose of this paper we treat it as a black box and concentrate on the measurement model for the fusion of *two* measurement sets.

As shown in Fig. 1, the two-dimensional random field (e.g., sea-surface) is constructed at the finest scale of a hierarchical tree, the nodes of which are indexed by variable s . Measurements are permitted at each finest-scale node on the tree:

$$y(s) = C(s)x(s) + v(s) \quad (1)$$

where C is some (user-determined) matrix, and v is white noise.

If the measurement sets are independent, with white measurement noise, then fusion is easy:

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} x(s) + \begin{bmatrix} v_1(s) \\ v_2(s) \end{bmatrix} \quad (2)$$

¹See <http://ocho.uwaterloo.ca>

Normally the difference between measurements is not white. The following two sections each explore one such case.

ATSR DAY / NIGHT FUSION

Obviously it would be desirable to use both day-time and night-time ATSR data in producing SST estimates, given the relatively sparse coverage of ATSR to begin with.

The challenge lies in the definition of SST: the infrared signal of the ocean is determined by the temperature of the skin (the top millimeter of water), rather than the bulk (the top meter measured by buoys). The skin–bulk difference is a relatively stable quantity at night, whereas the difference is affected by spatially-variable winds and solar heating during the day. If we chose the night-time skin temperature as our frame of reference, then we have

$$y_{NIGHT}(s) = t_{SKIN-N}(s) + v_1(s) \quad (3)$$

$$y_{DAY}(s) = t_{SKIN-N}(s) + t_{D-N}(s) + v_2(s) \quad (4)$$

where t_{D-N} is a highly-correlated random field, reflecting the day-night differences in the skin temperature, determined largely by atmospheric conditions.

ATSR / AVHRR FUSION

The case for fusing ATSR and AVHRR data is even stronger, in that it presents a unique opportunity to the strengths of both instruments, the atmospheric correction of ATSR and the dense coverage of AVHRR, to produce a superior SST map.

The challenge in this case lies in understanding the difference between the two measurement sets. It is reasonable to model ATSR night-time as accurate measurements of the SST skin:

$$y_{ATSR}(s) = t_{SKIN-N}(s) + v_1(s) \quad (5)$$

The AVHRR instrument measures the SST skin, corrupted by atmospheric effects (in particular its moisture content):

$$y_{AVHRR}(s) = t_{SKIN-N}(s) + t_{ATMOS}(s) + v_2(s) \quad (6)$$

We can rewrite the above measurement equations in the form of (1):

$$\begin{bmatrix} y_{ATSR} \\ y_{AVHRR} \end{bmatrix} (s) = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} t_{SKIN-N} \\ t_{ATMOS} \end{bmatrix} (s) + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} (s). \quad (7)$$

Our multiscale estimator is thus required to estimate the joint random fields t_{SKIN-N}, t_{ATMOS} , which can be accommodated as long as the joint statistics are known.

We model t_{SKIN-N} , representing the SST, with a relatively short, exponentially-shaped, correlation length. The

second random field, t_{ATMOS} , representing the atmospheric distortion, has a relatively long, Gaussian-shaped, correlation length. The two fields are modeled as being uncorrelated.

RESULTS

Fig. 2 shows the application of the multiscale fusion method to global ATSR and/or AVHRR data; the left column showing ATSR day / night fusion, and the right column ATSR / AVHRR fusion.

Panels (c) and (d) represent the “corrupted” measurements. Panel (c) shows the daytime ATSR measurements, which are clearly warmer (redder) than their nighttime counterparts in (a) due to solar warming. The AVHRR measurements in (d) appear similar to the more accurate measurements in (b), with the exception of large-scale, slowly-varying distortions which appear *very* clearly in the estimated atmospheric difference field in (h).

Of particular interest are the estimation error variances. In (i), despite the availability of both daytime and nighttime ATSR data, the short correlation length of the ocean leads to relatively poor estimates between the ATSR tracks. That is, fusion is only marginally successful.

On the other hand, fusing with much denser AVHRR measurements leads to almost uniform estimation uncertainty (j), because of two fortunate circumstances: first, that the gaps in the ATSR data are small relative to the atmospheric correlation length, and second, that the gaps in the AVHRR data are small relative to the oceanographic correlation length. Together these factors lead to estimates (f),(j) substantially superior to those produced by either instrument on its own.

References

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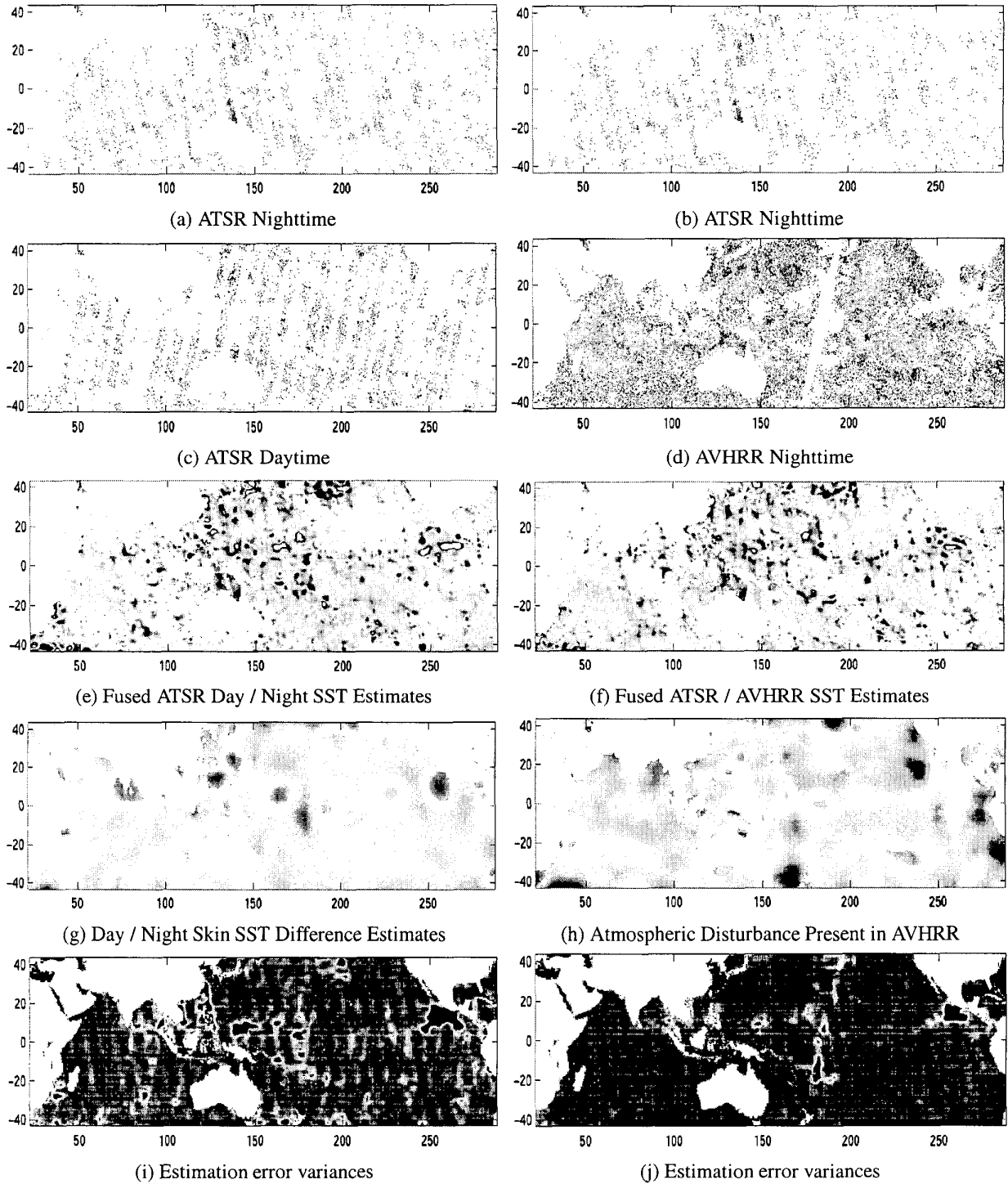


Figure 2: The top two rows show the input data (left: ATSR daytime/nighttime, right: ATSR/AVHRR) to be fused; the input data are the measured SST, with the annual mean removed. The fused SST estimates are shown in the third panel, with the *difference* estimates are shown in the fourth panel: (g) ATSR day–night difference estimates, (h) AVHRR atmospheric distortion estimates. Finally, the estimation error variances are plotted in the bottom panel.