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Satellite remote sensing of turbulent heat fluxes

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सार – इस शोध–पत्र में उपग्रह के आँकड़ों से प्रक्षुब्ध ताप फलक्सों का पता लगाने में हाल ही में हुई प्रगति और उनमें मौजूद समस्याओं की समीक्षा की गई है। महासागर वायुमंडल परिसंचरण के युग्मित निदर्शों का मूल्यांकन करने के लिए उपग्रह से प्राप्त फलक्स फील्ड अनिवार्य है। ये महासागर निदर्शों के लिए प्रणोदन प्रदान कर सकते हैं तथा इनमें महासागर और वायुमंडल के मध्य उष्मा और संवेग के आदान–प्रदान से आकाशीय और स्थानिक परिवर्तनशीलता को अच्छे से समझाने की संभावना होती है। इस अध्ययन का मुख्यकेंद्र बिंदु इनका संक्षेपण है, कि कौन से डाटा सेट पहले से विद्यमान हैं और उन्हें प्राप्त करने के लिए किन तकनीकों का उपयोग किया गया है। प्रकीर्णनमापी और पेसिव सूक्ष्म तरंग रेडियोमीटरों से प्राप्त धरातल की पवन गति का मूल्यांकन करने में पिछले दशक में काफी प्रगति हुई है। वायु आर्द्रता और वायुतापमान प्राप्त करने की पद्धतियों में अभी भी समस्या आती है। विद्यमान भूमंडलीय उपग्रह से प्राप्त डाटा सेटों की परस्पर तुलना करने से यह पता चला है कि इनमें क्षेत्रीय अंतर काफी अधिक है। तथापि उपग्रह के आँकड़ों के मध्य अनुरूपता, वहीं पर सुस्थापित एवं पुनः विश्लेषित डाटा सेटों से कहीं अधिक अच्छे हैं। इसीलिए यह आवश्यक है कि आँकड़ों के इन सभी तीनों प्रकारों की गुणवत्ता को विकसित करने के लिए मूल्यांकन किया जाए। समुद्री अभिवाह के इनिशिएटिवस् कम से कम बहुत अच्छा डाटा बेस और मौजूद डाटा सेटों के साथ ही साथ पक्सिल स्केल पर रिट्रिवल्स की गुणवत्ता का आकलन करने के लिए उपयुक्त ढाँचा प्रदान करते हैं।

ABSTRACT. This paper reviews recent progress and remaining problems in the derivation of turbulent heat fluxes from satellite data. Satellite derived flux fields are important for the evaluation of coupled ocean-atmosphere circulation models, they can provide forcing for ocean models, and have the potential to better understand the spatial and temporal variability of the exchange of heat and momentum between ocean and atmosphere. Here the focus is on summarising which data sets already exist and what techniques were used to derive them. Estimates of surface wind speeds from scatterometers and passive microwave radiometers made large progress over the last decade. Somewhat troublesome are still the methods for deriving air humidity and air temperature. Comparisons of existing global satellite derived data sets among each other revealed large regional differences. However, the agreement among the satellite data sets is much better than that with well established *in situ* and reanalysis data sets. Therefore it is necessary to foster assessments of the quality of all three kinds of data. The SEAFLUX initiative provides at least a very good database and builds a suitable framework to assess the quality of existing data sets as well as retrievals on the pixel scale.

Key words – Satellite remote sensing, Turbulent heat flux, Microwave radiometry, Remote sensing.

1. Introduction

The working group on air-sea fluxes jointly established by the World Climate Research Program's Joint Scientific Committee and the Scientific Committee on Oceanic Research has identified four classes of requirements for ocean-atmosphere heat flux estimates defined by different types of studies (WCRP, 2000). These are flux fields on high time and space resolution, typically 3 hours and 50 km, needed for example for forcing ocean circulation models or for regional weather nowcasting and prediction. The second class is for flux fields on longer space and time scales but with high absolute accuracy probably useful for the evaluation of climate models. A third class is defined by climate variability studies where again a high absolute accuracy is desirable but consistency and continuity over long time periods is the primary need. The final requirement is for high quality verification data needed by Numerical Weather Prediction models to verify the model physics through the use of independent estimates of the basic meteorological variables and the surface fluxes.

Satellite derived flux fields have the potential to be useful for all of these classes. Future satellite missions will deliver better temporal and spatial resolutions so that those data will be applicable for the first class. An example for such a mission concept is the Global Precipitation Mission targeting at passive microwave observations with a three hourly resolution for precipitation analysis. The length of the time period of available satellite data for radiation and turbulent flux determination has significantly increased, but great care is needed to provide flux estimates from sensors on successive satellites or from combinations of similar sensors on different satellites to ensure that the final product may be useful for the detection of long-term trends in the surface fluxes. At the moment the length of the time record of satellite-derived turbulent heat fluxes allows only for analysing annual and interannual variability which might be useful for evaluating climate models. In this context any improvement of the flux estimates itself through improved sensors, sensor combination, or better algorithms is meaningful.

Many algorithms have been developed for deriving basic state variables like sea surface temperature, atmospheric surface temperature, wind speed, atmospheric humidity, cloud liquid water, rain rate, longwave and shortwave radiation etc. from satellite data using instruments measuring at different wavelengths. Whereas the radiative fluxes at the surface are deduced from the radiative fluxes at the top of the atmosphere by using radiation transport models, turbulent heat fluxes are mostly estimated from the basic state variables using bulk flux algorithms (Fairall *et al.*, 1996). A comprehensive comparison of different bulk flux algorithms can be found in Zeng *et al.* (1998) and Brunke *et al.* (2002) and is not a subject of this paper.

Today, most of the basic state variables necessary for estimating surface fluxes can be derived from satellite data. These quantities may be directly derived using radar backscatter or from visible, infrared or microwave brightness temperatures. The exception is atmospheric surface air temperature where only first empirical algorithms came up recently. Air temperature is important to estimate the sensible heat flux and the transfer coefficients within the bulk approach but estimation from satellite data is still troublesome. Previously, some of these retrievals have been used to derive exemplary fields of the basic state variables over short time periods. However there has been a remarkable development of new algorithms which is gradually improving the situation.

The next section is describing suitable satellite data sources used for the derivation of turbulent heat flux fields. Section 3 introduces today's state of the art data sets of satellite-derived turbulent heat fluxes and the fourth section analyses the used basic state variable retrievals followed by a description of validation activities done for the HOAPS data set (Jost *et al.*, 2002, Graßl *et al.*, 2000) in section 5. Section 6 gives some conclusions and discusses necessary actions to improve those fields in the future.

TABLE 1

Temporal coverage of AVHRR

NOAA platform	Period of operation
TIROS-N	October 1978 – January 1980
NOAA-6	June 1979 – March 1983 and July 1984 – November 1986
NOAA-7	August 1981 – February 1985
NOAA-8	May 1983 – June 1984 and July 1985 – October 1985
NOAA-9	February 1985 – May 1994
NOAA-10	November 1986 – September 1991
NOAA-11	November 1988 – September 1994
NOAA-12	September 1991 – present
NOAA-14	December 1994 - present
NOAA-15	May 1998 - present
NOAA-16	September 2000 - present
NOAA-17	June 2002 – present

2. Satellite data sources

A major demand on the instruments utilised for the production of longer time series of flux estimates are accurate and relatively stable measurements over a long period. This is only attainable by using on-board calibration, applying algorithms that consider the ageing of the particular radiometer, or by applying ongoing calibration of the retrieved quantity with high quality *in situ* data. A further requirement, for instruments on polar orbiters, is that the swath width must be large enough (over 1000 km) to sample the earth's surface during a couple of days.

The classical instruments that meet the above requirements are the AVHRR and the SSM/I and similar instruments like the TMI on the TRMM satellite or the new AMSR. The AVHRR instrument has been flown on the NOAA satellite series since 1979 and used to construct global fields of sea surface temperature, for example the optimally interpolated SST data set of Reynolds (Reynolds and Smith, 1994) or the NOAA/NASA Oceans Pathfinder Sea Surface Temperature data set (Brown *et al.*, 1993). Flight periods for the different NOAA satellites are shown in Table 1.

The AVHRR instrument measures in five channels, two in the solar spectral range one in the near infrared, and two located within the infrared atmospheric window. The window channels are best suited for estimates of SST in cloud free cases. Despite the broad swath of ~3000 km, a complete coverage of the Earth surface is only achieved within one or two weeks depending on the actual cloud coverage. The quality of SST estimates is highly dependent on the quality of the implemented aerosol and cloud detection schemes. A description of possible errors can be found in Reynolds (1993).

One of the most advanced sensors for monitoring flux related atmospheric variables (wind speed and humidity) and ice cover from space is the SSM/I onboard the satellites of the Defence Meteorological Satellite Program. The SSM/I is a passive microwave radiometer measuring emitted radiation from the Earth's surface and the atmosphere at four frequencies located at 19.35, 22.235, 37.0, and 85.5 GHz at two polarisations (with the exception of 22 GHz which is only measured at vertical polarisation). The SSM/I instrument scans conically at a constant earth incidence angle of 53.1° resulting in a swath width of nearly 1400 km, only half of that of the AVHRR. However, cloud coverage is less of a problem within the microwave spectral range, so the determination of flux related variables is only hindered in cases when rain occurs.

SSM/I data are sampled every 25 km (A-Scan) at the three lower frequencies and every 12.5 km at 85.5 GHz. Most of the retrieval schemes rely upon the A-Scan data and do not consider the effects of different ground resolutions at different frequencies. The most comprehensive description of the instrument can be found in Hollinger *et al.* (1987).

SSM/Is have been flown on different DMSP satellites since July 1987 as shown in Table 2. These satellites have different orbits resulting in different local observing times which can have implications for the construction of a climatology. If the data from only one satellite is used (as has been done in many climatologies) sampling errors can result, at least in all quantities that have a distinct diurnal cycle.

TABLE 2

Temporal coverage of SSM/I

DMSP platform	Period of operation
F8	July 1987 – August 1991
F10	November 1990 – November 1997
F11	December 1991 – August 2000
F12	August 1994 (SSM/I failed soon after launch)
F13	March 1995 - present
F14	May 1997 - present
F15	December 1999 - present

3. State of the art data sets

Recently, several new climatologies of turbulent heat fluxes at the sea surface have been derived from above mentioned satellite data (Chou *et al.*, 1997; Jones *et al.*, 2001; Graßl *et al.*, 2000; Kubota *et al.*, 2002, Jost *et al.*, 2002). Table 3 gives names and some details about the available data sets. In most of them the fluxes were computed using bulk schemes with the basic state variables sea surface temperature, near surface air specific humidity and wind speed as input. Wind speeds were derived from passive microwave radiometer data or scatterometer data or both whereas the air humidity is derived from passive microwave radiometer data using algorithms described in the next section. For the sea surface temperature either AVHRR data or reanalysis products have been used. The temporal and spatial resolutions of the data sets vary from daily to monthly and from 0.25°×0.25° to 2°×2.5°. Comparisons of different satellite-derived data sets reveal a good agreement but also show large differences on the regional scale, *e.g.* HOAPS and the J-OFURO differ systematically in latent heat flux throughout the tropics by ~60 Wm^{-2} which is caused by different wind speed algorithms and a different sea surface temperature (Kubota *et al.*, 2002). J-OFURO and NASA's GSSTF differ much less because both are using the Wentz wind speed data set. However, the agreement among the satellite-derived data sets is much larger than that to ECMWF and NCEP re-analysis products or climatologies derived from *in situ* data (da Silva, 1994; Josey *et al.* 1999).

The existing satellite-derived data sets cover different periods and also contain different flux fields. The HOAPS data set is the only one also comprising precipitation and freshwater flux estimates whereas the J-OFURO data set is the only one that contains estimates of shortwave radiation fluxes. From this we can say that all data sets together show a potential to derive the net energy flux as well as the freshwater flux at the same time.

4. Basic variables retrieval algorithms

Because the focus of this review is on turbulent heat fluxes, this paragraph gives an overview about the methodology of the satellite retrievals used for deriving the basic state variables necessary for the bulk approach used to compute turbulent heat fluxes.

TABLE 3

Available global data sets of monthly mean satellite derived energy fluxes at the sea surface

Name	Time period	Spatial resolution (Lat. × Long.)	Basic state variable retrieval
ANN Jones *et al*., 1999	01/88- 2000	0.25°× 0.25°	u: Wentz (1997) q_a: Jones *et al*. (1999) SST: NCEP reanalysis T_a: Jones *et al*. (1999)
GSSTF Chou *et al*. (1997)	07/87-12/94	2°×2.5°	u: Wentz (1997) q_a: Modified Schulz *et al*. (1993) SST: NCEP reanalysis T_a: NCEP reanalysis
HOAPS Jost *et al*. (2002); Graßl *et al*. (2000)	07/87-12/99	1°×1°	u: Schlüssel and Luthardt (1991) q_a: Schlüssel *et al*. (1995) SST: NOAA Pathfinder T_a: 80% relative humidity at q_a
J-OFURO Kubota *et al*. (2002)	01/91-12/95	1°×1°	u: Wentz *et al*.(1997) q_a: Schlüssel *et al*. (1995) SST: OI Reynolds and Smith (1994) T_a: Bowen ratio (Kubota and Mitsumori, 1997)

4.1. *Sea surface temperature*

Infrared radiometers carried by satellites provide the potential for SST measurements over the global ocean on a regular basis. Unfortunately, at any time significant areas of the ocean are cloud covered and data from different over-passes must be composited. Atmospheric water vapour, aerosols, and clouds have all the potential to significantly bias the data unless adequate correction procedures are implemented. Reliable cloud clearance remains a problem, as does the effect of sub-pixel cloudiness. The measurements rely upon a small number of sensors with the possibility of changes in sensor characteristic between satellites.

Accurate operational SST retrievals from the AVHRR carried on the NOAA series of polar orbiting satellites have been available since late 1981 (Reynolds, 1999). The error budget for the AVHRR is dominated by the instrument calibration accuracy and atmospheric transmission effects. Thus the instrument must be calibrated against drifting buoys and the calibration accuracy continually verified. Walton *et al*. (1998) reviewed the algorithms used which are different depending on whether it is day or night. They found that the daytime rms accuracy (compared to drifting buoy data) had improved from 0.8° C in 1989 to 0.5° C in 1998, whereas the night time rms had remained constant at about 0.5° C. The bias was normally between –0.2° C to + 0.4° C. However larger errors can occur due to changes in atmospheric aerosol loading. For example the eruption of Mount Pinatubo resulted in a regional cold bias of order 2° C over much of a two year period. Explicit water vapour corrections using SSM/I derived vertically integrated water vapour content (or "precipitable water") have been tested and shown to be successful (Emery *et al*., 1994); however they have not been implemented operationally.

Estimates of sea surface temperature with not much less accuracy are also possible employing passive microwave measurements at frequencies between ~5-10 GHz that are available from TRMM's TMI (Wentz *et al*., 2000) and will shortly be available from the AMSR onboard the Aqua and ADEOS-II satellites. The big advantage of those estimates is the much better coverage because clouds are almost transparent at those frequencies allowing an undisturbed view of the ocean surface. However, infrared estimates of sea surface temperature remain of high importance for the computation of evaporation climatology because estimates of sea surface temperature from SSM/I measurements were not possible with sufficient accuracy.

4.2. *Air temperature from SSM/I*

The near-surface air temperature T_a enters the bulk formula for sensible and latent heat fluxes in different ways. It is needed directly to determine the air-sea temperature difference in the computation of sensible heat flux. But it is also involved in the computation of exchange coefficients, air density and latent heat of evaporation for both turbulent heat fluxes. Because there is no means to directly access the air temperature from the satellite measurements currently used for heat flux estimation, some indirect methods of varying accuracy have been developed.

A very simple method is to assume slightly unstable conditions at any location at any time and set $T_a = T_S - 1$, where T_S is the sea surface temperature. The results of Wells and King-Hele (1990) show that most of the observed air-sea temperature differences in the tropical oceans are in the order of 1°C. However if, instead of the assumed unstable conditions, stable conditions occur, the exchange coefficient for latent heat flux will be underestimated at low wind speeds by ~50% (Schulz *et al.*, 1997). Another simple method is to compute T_a from the retrieved specific air humidity assuming a constant relative humidity, *e.g.* 80% (Liu, 1988) or using a climatological relative humidity. This might be accurate enough to compute the exchange coefficients but seems to be too rough an estimate to determine sensible heat flux.

A more sophisticated approach using a relationship between T_S and the Bowen ratio at long time scales (compared to the synoptic time scale) has been undertaken by Konda *et al.* (1996). This work is based on the previous work of Hicks and Hess (1977) who established this relationship from experimental data. Their aim was the reconstruction of the sea surface skin temperature (rather than the bulk temperature measured by ships) in order to compute long term averages of the turbulent fluxes more correctly. Adapted from Konda *et al.* (1996) the turbulent heat fluxes can be written as:

$$H = -\rho c_p K_H \left(\frac{\partial T_a}{\partial z} \right); \qquad E = -\rho L K_E \left(\frac{\partial q}{\partial z} \right) \tag{1}$$

where ρ is the air density, L is the latent heat of evaporation, c_P is the specific heat at constant pressure, K_H and K_E are the diffusivity coefficients of heat and humidity, T_a is air temperature, and q specific humidity. Assuming that $K_H = K_E$ we obtain for the Bowen ratio :

$$\beta = \frac{H}{E} = \frac{c_p}{L} \frac{\partial T_a}{\partial q} \tag{2}$$

If one uses the bulk formulae for the fluxes the Bowen ratio reads:

$$\beta = \frac{c_p C_H (T_0 - T_z)}{L C_E (q_0 - q_z)} \tag{3}$$

where C_H and C_E are the bulk transfer coefficients and the indices 0 and z denote values at the sea surface and at the reference level over the surface, respectively. Eqns. (2) and (3) together give:

$$\frac{L}{c_p} \left. \frac{\partial q}{\partial T_a} \right|_{T=T_z} = \frac{L C_E (q_0 - q_z)}{c_p C_H (T_0 - T_z)} \tag{4}$$

If q is written as α $q_S(T)$ with α relative humidity and $q_S(T)$ denoting the saturation humidity function Eqn. (4) can be written as:

$$\frac{C_E (q_0 - q_z)}{C_H (T_0 - T_z)} = \frac{q_z}{q_S(T_z)} \left. \frac{\partial q_S(T_z)}{\partial T} \right|_{T=T_z} + q_S(T_z) \left. \frac{\partial \alpha}{\partial T} \right|_{T=T_z} \tag{5}$$

The second term on the right hand side of Eqn. (5) has been neglected by Konda *et al.* (1996) because it is much smaller than the first term and it is not directly determinable from satellite or buoy measurements.

Using the empirical relationship between total precipitable water, obtained from SSM/I measurements and near-surface humidity established by Liu (1986) and AVHRR multichannel sea surface temperatures adjusted to skin temperatures, T_a can be computed from Eqn. (5). The error of a monthly mean satellite-derived air temperature is then approximately -0.3 ± 3.1° C as found by comparison to TOGA TAO buoys and buoys of the Japan Meteorological Agency. This accuracy is not high enough to study sensible heat fluxes on a monthly scale, but can be useful for analysing interannual variations. Improvements to this technique by using further developments of the retrieval schemes for T_S and q have not been explored. However, comparison with the approach based on the assumption of a constant relative humidity show that the Konda *et al.* (1996) approach is better in bias and rms error.

A recent paper by Jones *et al.* (1999) tried to invert monthly means of T_a from SSM/I measurements of total precipitable water W and sea surface temperature, T_S, analysis from NCEP using neural network techniques. The network was trained with data extracted from the Surface Marine Data provided by da Silva (1994). The neural network was used in a sort of double loop where in the first round the network was trained only with W and T_S and in the second round the bias between the algorithm's outcome and the truth data set was used as a third input parameter for the network. From this procedure it was not surprising that the global mean bias between the T_a produced by the network and the da Silva data set was negligible. The global rms was stated to be 0.72 ± 0.38° C which is much lower than the results obtained with the Konda *et al.* (1996) method or the method of Jourdan and

Gautier (1995) who obtained a global rms error of 2.6 ± 1.4° C from a polynomial fit between W and T_a. However, a criticism is that the da Silva (1994) data set was regarded as ground truth. Given the large differences between *in situ* climatologies found by Josey *et al*. (1999), compared to independent high quality buoy measurements, this may not be appropriate. Since the satellite-derived data sets are expected to improve on the *in situ* climatologies a real challenge for verification would be to compare with the independent long term buoy data sets like that of the Subduction experiment (Moyer and Weller, 1997).

4.3. *Near surface humidity*

Because the interaction of the radiation field with water vapour at a distinct level is not measurable, all methods determining the near-surface humidity make use of a vertically integrated water vapour content (obtained from a passive microwave instrument such as the SSM/I) as a predictor for the near-surface specific humidity, q, required for the bulk approach. The correlation between both quantities depends heavily on the time scale considered. At any given time, Schlüssel (1989) showed that the total precipitable water, W, is only weakly correlated to q. He computed the correlation coefficients between adjacent atmospheric layers and atmospheric layers separated by a distance of 50 hPa or more. Vertical profiles of the correlation coefficient were larger than 0.9 for adjacent layers and values larger than 0.8 for layers with a separation distance of 50 hPa. However, the correlation profile always exhibited a significant minimum near the mean height of the atmospheric boundary layer whenever the distance between the layers was larger than 50 hPa. This indicates a decoupling of the moisture in the boundary layer from that in the free troposphere. Liu (1990) found similar results when he examined vertical variance profiles of semi-daily and daily radiosonde ascents for two tropical stations and one station in mid-latitudes. All three variance profiles showed a maximum at approximately 800 hPa caused by varying atmospheric boundary layer height and a varying contrast with the water vapour content above the boundary layer. The variance maximums as well as the correlation minimum are much less distinct if monthly averages are considered. This is the reason why Liu and Niiler (1984) had success establishing the polynomial relationship between monthly averages of q and W.

The method of Liu and Niiler (1984) determines the monthly marine surface-layer humidity with a simple polynomial regression of q *versus* W. The relation was found by examining radiosonde data from 11 mid-ocean island stations and weather ships scattered over the Atlantic and the Pacific Ocean. The accuracy stated for a globally regression formula was 0.8 gkg^{-1} (Liu, 1986) and 1 gkg^{-1} (Liu *et al*., 1991) depending on the validation data source. This simple formula can be used with any retrieval algorithm which determines W, for example that of Schlüssel and Emery (1990):

$$W = k_0 + k_1 \ln(280 - T_v^{22}) + k_2 (\ln(280 - T_v^{22}) - T_v^{37}) \quad (6)$$

which has an accuracy of 1.5 kg m^{-2} for instantaneous SSM/I measurements. Upper indices on temperature denote the SSM/I channel and the lower index stands for the polarisation. Some scientists have tried to use this method for the production of daily values of q but, as may be expected from the previous discussion, this reduces the accuracy in q so much that the result becomes more or less useless.

Because of the inability of Liu's method to determine q for individual situations, Schulz *et al*. (1993) developed a new method that first derives the integrated water vapour content of the atmospheric boundary layer w_B (using a somewhat artificial height of 500 m) and then deduces q with a simple linear regression from w_B. Schulz *et al*. (1993) showed that w_B can be independently retrieved from W and that the correlation between q and w_B is much higher than that with W. Schlüssel *et al*. (1995) improved this technique slightly by obtaining the specific humidity directly from the brightness temperatures, thus avoiding the error propagation that occurs in the two-step method. The standard error for this globally valid retrieval is stated to be 1.1 g kg^{-1} for an instantaneous SSM/I measurement. Comprehensive comparisons have been made by Schlüssel (1995) and Schulz *et al*. (1997), using data from merchant ships, OWS and scientific experiments. They confirmed the global validity of this method and found rms errors not much higher than the stated retrieval error. A large portion of error was due to the mismatch of the measurements in time and space as shown by Wentz (1997). However, a problem was found over tropical oceans where a systematic overestimation of q occurred if the mid-tropospheric humidity was high. Schulz *et al*. (1997) reported that the correlation between the surface q and the water vapour content in the lowest 500 m of the atmosphere was much lower than that for extratropical atmospheres. A reason might be that a 500 m layer does not represent the boundary layer depth in a case of convective activity and high mid-tropospheric humidity very well. Schlüssel and Albert (2001) adapted this concept to TRMM's TMI and found similar errors compared with the use of the SSM/I.

Recently, an alternative approach has been reported by Chou *et al*. (1995; 1997). They estimated q from the total water vapour content W and w_B, retrieved with the algorithms of Wentz (1989) for W and Schulz *et al*. (1993) w_B, using an EOF (empirical orthogonal function) method with different EOF's for six classes of W. The accuracy attained for q was not much different from the Schulz *et al*. (1993) method since the weights for w_B in the EOF analysis were two orders of magnitude larger than those for W. Some corrections were introduced for dry and wet biases occurring respectively at the low and high end of the humidity spectrum. At the low end, Chou *et al*. (1997) only used W within the EOF analysis to correct for an underestimation of q during wintertime over extratropical oceans. The other correction concerned a positive humidity bias during summer in regions where warm air moves over a colder ocean surface. In that case they constrained the surface air humidity to the saturation humidity at sea surface temperature. A side effect of this was that, in each case with an overestimated w_B, a positive bias will be automatically corrected.

As for the near-surface air temperature Jones *et al*. (1999) used a neural network to obtain monthly averages of q. Input to the neural network were W and sea-surface temperature extracted from the Surface Marine Data provided by da Silva (1994) and the monthly averages of SSM/I brightness temperatures on a 1° × 1° grid. Since the bias between satellite derived q and *in situ* data is incorporated in a second loop of the neural network, again it is not surprising that this method showed no bias when compared to the da Silva data set. The global rms error stated is 0.77 gkg^{-1} with smaller errors in the North Atlantic and in the North Pacific (0.6 gkg^{-1}) and larger errors in the southern Indian, Pacific and Atlantic Oceans (1.2 gkg^{-1}) reflecting the small observation density in the da Silva data set in those regions. This method was only compared to that of Liu (1986) and showed the expected improvement. Recently this method has been extended to daily averages in the tropical oceans using TAO buoys instead of reanalysis data as input for the neural network (Jones *et al*., 2001). Comparisons to Chou's and Schulz's methods and to independent *in situ* measurements are necessary to evaluate this method more carefully.

4.4. *Wind*

(*i*) *Scatterometric wind vectors*

Wind vector estimates from scatterometers are based on empirical relationships (model function) relating backscattered energy to wind speed at 10 m under neutral conditions. Geophysical validation over a wide range of wind speeds has been difficult due to (a) the difficulty in acquiring suitable *in situ* observations and (b) the inherent incompability between scatterometer measurements and buoy observations (Freilich and Dunbar, 1999). However the model functions have improved over time with the introduction of more sophisticated techniques and also as more scatterometer and high quality *in situ* data become available to test the full parameter space of the backscatter-wind relationship. Scatterometer data are available from numerous sources (each using a different model function). Thus it is important to note the particular version and source of scatterometer data.

The fundamental scatterometer design results in multiple possible wind directions from which the most likely solution is determined. This ambiguity selection process is fairly accurate; for regions with rms wind speed greater than 4 ms^{-1}, the NSCAT ambiguity removal skill is conservatively estimated to be 95% (Gonzales and Long, 1999). The sampling characteristic (number and width of data swaths, data coverage) of the scatterometer data govern the ability to estimate synoptic fields of winds.

The accuracy of the scatterometers is relatively excellent compared to errors for winds from VOS. Validation of the CERSAT ERS-1/2 scatterometer wind retrievals found a systematic underestimation of nearly 0.75 ms^{-1} and an rms error of ~1.3 ms^{-1} (Graber *et al*., 1996). Directional biases and rms errors were ~7° and ~22° respectively. Other comparisons further explore such dependencies as wind direction on incidence angle(Ebuchi and Graber, 1998) and validation in coastal seas (Kent *et al*, 1998).

Evaluation of the 25-km NSCAT instrument winds has been much more comprehensive. Compared to high-quality ship winds (Bourassa *et al*., 1997), the NSCAT winds had rms differences for speed and direction of 1.8 ms^{-1} and 14°. When compared to buoys, the bias was ~0.3 ms^{-1} and rms error ~1.3 ms^{-1} (Freilich and Dunbar, 1999). Other validations are available and include a wide range of approaches, including gridded product evaluation through direct comparison to other products (Atlas *et al*., 1999); comparison of ocean models forced by various products (Verschell *et al*., 1999); and comparisons for use in air-sea carbon exchange (Boutin *et al*., 1999).

(*ii*) *Passive microwave surface wind speeds*

Thermal radiation emitted by the sea surface at millimeter frequencies is strongly modified by wind-induced sea surface roughness and partial foam coverage. The classical description of the emissivity of a foam covered rough ocean surface as a function of frequency ν, incident angle θ_i, polarization P, wind speed u, and fractional foam coverage C_f is :

$$\varepsilon(\upsilon,\theta_i,P;u,C_f) = (1-C_f)\varepsilon_{rw}(\nu,\theta_i,P;u) + C_f\varepsilon_f(\nu,\theta_i,P) \quad (7)$$

where ε_{rw} is the emissivity of a wind roughened surface, and ε_f is the emissivity of foam. In the algorithm development history different theoretical and empirical models have been used to relate C_f, ε_{rw}, and ε_f to the physical state variables of the sea surface and to the wind field above. In the material that follows four types of wind speed algorithms for the SSM/I are described. These are the modified D-Matrix approach by Goodberlet and Swift (1989), the radiation transport model and regression based algorithm of Schlüssel and Luthardt (1991), neural network algorithms by Stogryn *et al*. (1994) and Krasnopolsky *et al*. (1995), and the wind speed part of the SSM/I all weather algorithm by Wentz (1997) and Wentz and Spencer (1998). The selection of these four algorithms does not cover all the available wind speed algorithms but it gives a description of different methodologies and a brief survey of the history of algorithm development.

The original D-Matrix algorithm as given in Lo (1983) computes the wind speed at a reference level of 19.5 m from a linear combination of SSM/I brightness temperatures. It uses 11 sets of coefficients representing particular seasons and latitude bands. Goodberlet and Swift (1989) found that the original D-Matrix algorithm did not meet the accuracy criteria of 2 ms^{-1} when results obtained from SSM/I measurements were compared to NOAA buoys. Additionally, they found a low bias at high wind speeds and zonal discontinuities due to the coefficient scheme used. They developed an alternative new D-Matrix algorithm from SSM/I brightness temperatures and buoy wind speeds using linear regression analysis that met the 2 ms^{-1} criterion for all seasons and latitude bands. Since this algorithm works only for rain free cases, the D-Matrix algorithm uses a rain flag system to discard affected measurements. Such an algorithm is quite robust but doesn't point the way to future improvements since it is purely statistical; no information on the influence on the measurements of the surface emissivities given in Eqn. (7), or of the atmospheric part of the signal, can be quantified. Goodberlet and Swift (1992) improved their algorithm with a nonlinear version that should account for waterladen atmospheres. As stated by Krasnopolsky *et al*. (1995) this retrieval has a singularity at Δ_{37} = 30.7 K which may fall within the useful range of brightness temperatures.

The Schlüssel and Luthardt (1991) algorithm is based on studying theoretically the radiative transport within the SSM/I channels for a large set of oceanic/atmospheric situations with respect to wind speed. The retrieval formula is derived by multivariate regression analysis from the simulated synthetic measurements. It derives the wind speed mainly from the brightness temperature difference between horizontally and vertically polarised components at the same frequency so it is, like the Goodberlet and Swift (1989) algorithm, a linear combination of SSM/I channels. The theoretical accuracy for the globally valid passive wind speed retrieval is stated to be 1.4 ms^{-1} under conditions where the satellite measurements are not affected by heavy rain.

This retrieval was evaluated by Schlüssel and Luthardt (1991) by comparing satellite derived wind speeds with objectively analysed *in situ* wind speeds over the North Sea (Luthardt, 1985) during the period July 1987 to June 1988. They obtained a standard error of 1.9 ms^{-1} with a small bias of 0.2 ms^{-1}. Schulz (1993) compared 3403 globally distributed buoy and ship measurements with retrieved wind speeds during the period July 1987 to September 1987 and found a standard error of 2.1 ms^{-1} with the same bias as over the North Sea. The systematic error is only significant at wind speeds above 15 ms^{-1} and could have been caused by an insufficient parameterisation of the emissivity of the ocean surface at high wind speeds. This is difficult to prove since there are only a few measurements during high wind speeds and moreover still fewer measurements of the emissivity in the microwave region under those conditions. However, this comparison revealed also that this algorithm produces a high bias of 0.81 ms^{-1} at latitudes between 20° N and the equator which show that the retrieval scheme is sensitive to liquid water in the atmosphere.

Consequently, (Schlüssel, 1995) modified this algorithm to allow more liquid water in the atmosphere during the radiative transport simulations and also determined new coefficients for the algorithm (using the same channels) if light rain is present. The choice of retrieval was decided using a rain flag system similar to Goodberlet and Swift (1989). The accuracy for the light rain retrieval was determined to be 1.6 ms^{-1}.

Neural network approaches are alternative empirical methods to derive wind speed from passive microwave brigthness temperatures which have become popular during the last ten years. Neural networks can be advantageous if :

(*i*) Nonlinearities occur in the transfer function, from brightness temperature to the sought geophysical parameter, which vary over the range of measurement space.

(ii) There is no a priori knowledge with regard to an analytical representation of the transfer function.

Stogryn *et al*. (1994) and Krasnopolsky *et al*. (1995) have developed neural network retrieval schemes that outperform all of the previously described algorithms. The biases and rms errors as stated by Krasnopolsky *et al*. (1995) are 0.05 ms^{-1} and around 1.6 ms^{-1} respectively, when compared to buoy measurements in their test data set. Krasnopolsky *et al*. (1995) introduced a new rain flag system that was based on liquid water content and which recovered 40% of measurements rejected by the Goodberlet rain flag system.

However, these algorithms can have limitations as :

(*i*) The training data sets must include enough low and high wind speed cases. Otherwise a high bias at low wind speed and a low bias at high wind speed occur and the variance of the wind speed distribution is too low. Especially, neural networks are not able to extrapolate which may lead to large negative biases at high wind speeds if those were not incorporated in the training data sets.

(*ii*) Neural networks are more sensitive to sensor-dependent systematic errors (like calibration). For example, Krasnopolsky *et al*. (1995) trained their network for the DMSP F8 satellite and when they apply their coefficients to data of the F11 satellite they obtained a bias of -0.9 ms^{-1} and a rms error of 1.85 ms^{-1} although the brigthness temperature differences between F8 and F11 are only ~1K for all channels. This effect can be diminished by computing coefficients for each satellite but should be kept in mind if neural networks are blindly applied.

With respect to equation (7) the same arguments hold as for the empirical regression algorithms if we ask for physical explanations of the change of surface emissivity with wind speed. As for any empirical algorithm, they may give good estimates of wind speed but little can be learnt about the physics. This could be changed if the neural network were not trained on buoy-satellite match ups but rather used in conjunction with radiative transfer models thus giving more control on the situations considered (Schlüssel and Albert, 2001).

The Wentz (1997) all weather algorithm represented a more physical approach in retrieving the wind speed from SSM/I measurements in rain free situations. Wind speed was retrieved, along with columnar water vapour and columnar cloud liquid water, using a nonlinear optimisation method. The wind-induced emissivity of the sea surface was parameterised by a two scale theory (Wu and Fung, 1972; Wentz, 1975) which was based on the knowledge of the root mean square slope of the large gravity waves, the standard deviation of the small irregularities, and the correlation length of the small surface structures. In practice, Wentz (1997) expresses the wind-induced emissivity as a monotonic function of wind speed which consists of two linear segments connected by a quadratic spline such that the function and the first derivatives in wind speed are continuous. The coefficients for this model were derived from collocated buoy and SSM/I observations.

Wentz (1997) also investigated the role of wind direction on the retrieval accuracy and found that errors of approximately 3 ms^{-1} can occur, especially if the radiometer looks in the upwind direction. He developed a correction of this effect which brought the error down to 0.5 ms^{-1}. Additionally, he claimed that the information on wind direction inherent to the SSM/I measurements can be retrieved if the signal to noise ratio can be enhanced by building averages over large scales and long times.

Importantly, Wentz (1997) also gave an error estimation that resolved the error budget in terms of model errors, wind direction errors, radiometer noise, sampling mismatch between satellite and buoys, and other errors that could not be resolved. This enabled him to subtract the sampling mismatch error from the total observed error. For his own retrieval he ended up with a small systematic error of 0.3 ms^{-1} and an rms accuracy of 0.9 ms^{-1}; significantly better than all previous algorithms.

In a new all weather algorithm (Wentz and Spencer, 1998) the retrieval methods are extended to rain cases. With respect to wind speed, this simply consists of discarding the retrieval and filling in values from neighbouring pixels, or using a monthly climatological value derived from SSM/I. This algorithm has been used to compute a 10 year time series of wind speed from the chain of SSM/I sensors which is, together with other atmospheric variables, available via the internet under http://www.ssmi.com.

5. Evaluation of the HOAPS data set

As an example for the existing satellite-derived turbulent flux climatologies here a part of the evaluation attempts of the HOAPS data set is presented. The HOAPS data set has been evaluated using a two way validation strategy. As a first step, each retrieval algorithm used has been validated with *in situ* data from different sources such as scientific experiments or data from the GTS. These intercomparisons focussed mostly on the quality of the retrievals, with the exception of using a sample of GTS data to compare on a monthly time scale but with very coarse spatial resolution Schulz *et al*. (1997). The second step focussed more on comparisons of the gridded data set to long term buoy measurements like the Subduction Experiment (Moyer and Weller, 1997) and on comparisons to global climatologies derived from *in situ* data, namely that of the Southampton Oceanography Centre (SOC – Josey *et al*., 1999). Especially the comparison to the *in situ* climatologies has been done by almost every flux data set producer. For the HOAPS data set this is described in detail in Jost *et al*. (2002). Here only the results of a comparison to the Subduction buoy data is presented because this type of comparison is of high importance because the buoy data can be characterised as the best available *in situ* data.

Because climatologies can not serve as a validation data set for each other, independent ground truth must be used for deeper analysis of errors. Josey *et al*. (1999) have used the data from the Subduction Experiment described by Moyer and Weller (1997) for verification. The same task has been repeated for the HOAPS climatology. Unfortunately, buoy arrays with very high quality measurements are not available at many locations in the oceans so that this comparison can only serve as a tool to identify possible regional biases in either climatology.

A time series consisted of monthly mean values from the Subduction buoys was compared with 1°×1° field data from the HOAPS data set. The time series at all buoys agreed fairly well with correlation coefficients greater than 0.95 for all basic state variables and a slightly lesser correlation for the derived fluxes. The variability of the bulk parameters within one month is almost of equal size for both data sets for all months during the two year period. That implies that even with only two satellite overpasses per day, it appears to be feasible to represent the intra-monthly variability of basic state variables-at least in the Subduction area. However, positive biases were found for wind speed at both northern buoys over the whole buoy deployment period. The reason for this bias can only be found through a comparison of the wind speed spectra derived from simultaneously measured buoy and SSM/I data. A possible reason can be an underestimation of the wind speed at the buoy because the sensors were installed at a height of 2-3 m so that the instruments can be in the wave trough region during high wind speed events. Negative biases were found for sea surface temperature at both southern moorings during the first year of the deployment period. The suggestion that this bias was caused by aerosols from the Mt Pinatubo eruption, and subsequent deterioration of the cloud screening in the AVHRR data set, seems to be unrealistic because this feature should be found at all buoy sites. Estimates of specific air humidity are almost bias free at all moorings during the deployment period.

The averages and mean differences between HOAPS and all five Subduction buoys are summarised in Table 4. The positive bias in wind speed resulted in overestimations of sensible and latent heat flux at the North East and the Centre buoy whereas the negative biases in sea surface temperature cause a negative bias in latent heat flux at both southern buoys. Although the bias for sensible heat flux equalled zero at three of the five buoys this should only be taken as an indication that crude assumptions, like a constant relative humidity of say 80% may be sufficient to determine a climatological mean value (rather than the annual cycle which appears somewhat exaggerated in the HOAPS data set). Estimates of longwave net flux are not generally biased low or high. Because of the dependence of the downwelling radiation on actual cloud cover, differences in satellite and buoy estimates can be caused by satellite resolution effects. The satellite instrument can't resolve the cloud spatial and time scales because of its coarse spatial resolution - only 30 - 70 km and only two measurements per day per satellite. All the more surprising is that the mean differences in net longwave fluxes between HOAPS and the buoys are not much larger than differences between buoy data and the SOC climatology.

Comparison of the mean differences between the HOAPS data set and the Subduction buoy measurements, for all fluxes and basic state variables, with the findings summarised in the study done by Josey *et al*. (1999) reveals that the satellite data set appears to be competitive with the *in situ* product even in this not too badly sampled region.

6. Summary and outstanding problems

This paper reviewed recent progress and remaining problems in the derivation of turbulent heat fluxes from satellite data. Satellite derived flux fields are important for the evaluation of coupled ocean-atmosphere circulation models, they can provide forcing for ocean models, and have the potential to better understand the spatial and temporal variability of the exchange of heat and momentum between ocean and atmosphere. Here the focus was on summarising which data sets already exist and what techniques were used to derive them.

The review of the existing data sets showed that there are four different satellite-derived data sets available where the length of the data record exceeds five years. The basis of all data sets is the outstanding SSM/I data record which allowed the derivation of long time series of geophysical variables. Some of the data sets rely purely on satellite data, parameterisations, and assumptions like HOAPS and J-OFURO others incorporate also fields from reanalysis data sets for SST and T_a.

With respect to the methods it is obvious that estimates of surface wind speeds from scatterometers and passive microwave radiometers have made large progress over the last decade. Somewhat troublesome are still the

TABLE 4

Mean heat fluxes and differences for the Subduction experiment buoy array

Location	Source	LH[1] Wm^{-2}	LE[2] Wm^{-2}	u[3] ms^{-1}	q_s[4] gkg^{-1}	q_a[5] gkg^{-1}	NLW[6] Wm^{-2}
NE Buoy, N=23 (33° N, 22° W)	HOAPS	14±9	102±24	6.7±1.2	15.2±2.4	11.2±2.0	74±12
	Buoy	9±4	97±20	5.5±0.6	15.2±2.4	11.1±2.0	66±8
	HOAPS-Buoy	5±9	5±21	1.2±0.8	0±0.3	0.1±0.7	8±10
SE Buoy, N=14 (18° N, 22° W)	HOAPS	7±21	95±53	7.3±0.7	15.9±1.4	12.5±2.1	84±26
	Buoy	7±3	103±25	7.3±0.8	16.6±1.5	13.0±1.6	47±16
	HOAPS-Buoy	0±20	-8±33	0±0.6	-0.8±0.6	-0.5±1.0	37±13
SW Buoy, N=14 (18° N, 34° W)	HOAPS	5±15	101±43	6.9±0.9	18.1±1.3	14.1±1.9	60±16
	Buoy	5±3	129±25	6.6±0.5	18.6±1.4	13.7±1.8	60±11
	HOAPS-Buoy	0±13	-28±28	0.3±0.7	-0.6±0.6	0.4±0.8	0±11
NW Buoy, N=13 (33° N, 34° W)	HOAPS	7±8	86±23	6.5±1.5	15.9±2.7	12.3±2.5	66±13
	Buoy	7±3	84±20	5.1±1.1	16.0±2.9	12.0±2.2	76±9
	HOAPS-Buoy	0±7	2±22	1.4±0.6	-0.1±0.3	0.3±0.5	-10±9
C Buoy, N=18 (25.5° N, 29° W)	HOAPS	16±10	116±27	6.5±0.8	16.6±1.7	12.1±1.8	76±12
	Buoy	7±3	107±18	5.7±0.8	16.8±1.8	12.2±1.8	66±13
	HOAPS-Buoy	9±8	9±18	0.7±0.5	-0.2±0.3	-0.1±0.6	11±13

[1]*LH* : Sensible Heat Flux in Wm^{-2}
[2]*LE* : Latent Heat Flux in Wm^{-2}
[3]*u* : Wind speed in ms^{-1}
[4]q_s : Specific saturation humidity at sea surface temperature in gkg^{-1}
[5]q_a : Specific air humidity at 10 m above sea level in gkg^{-1}
[6]*NLW* : Net longwave radiative flux at the sea surface in Wm^{-2}

methods for deriving air humidity and air temperature. Air humidity estimates from precipitable water of the lower troposphere represent still better estimates than microwave humidity sounders. Although some new statistical techniques (ANN) were developed to derive air temperature from SSM/I measurements, it seems difficult to improve upon numerical weather prediction models until new improved profiling capability will be available.

The exemplary comparison exercise of the HOAPS data set with the high quality *in situ* data set of the Subduction buoys revealed that at least the derivation of latent heat flux is competitive to fields derived from COADS data with a much better coverage of the global ocean. Comparisons of existing global satellite derived data sets among each other revealed large regional differences. However, the agreement among the satellite data sets is much better than that with well established *in situ* and reanalysis data sets indicating a convergence of the satellite data sets.

The WCRP/SCOR working group on air-sea fluxes released several recommendations to improve flux estimates in general during their final workshop in June 2001 (WCRP, 2001). Relevant for satellite-derived fluxes are:

(*i*) The flux data sets need both direct and indirect validation. Direct validation requires high quality *in situ* observations such as the Subduction buoys, oceanic research ships, high-density hydrographic data and selected satellite data. For example passive microwave wind estimates may be validated using scatterometer data. Indirect validation can be done by inter comparison of different data sets, use in ocean circulation and inverse models, and comparisons to inverse or derived heat balances.

(*ii*) During any comparison activity it should kept in mind that the variability of data sets compared plays an important role. A consequence of this is that data sets of different spatial resolution say fields and point measurements cannot be compared directly, because the result would be that the lower resolution data set overestimates low values and underestimates high values. So in the case of comparison of instantaneous satellite retrievals and buoy measurements, the buoy data have to be averaged in time to reduce their variance. However it is difficult to determine which temporal scale corresponds to the spatial resolution of the satellite data set.

(*iii*) Flux fields need to be accompanied by error estimates. Data assimilation is becoming omnipresent and needs the structure of errors on different scales as well as the spatial distribution.

(*iv*) Improvements are expected through the combination of flux and meteorological products from different sources emphasizing the individual strength of the used data sources. This implies that an inventory of available and required flux and basic state variables data sets exist and is maintained.

(*v*) Strong support has to be given to initiatives like SEAFLUX (Curry *et al*., 2002) which provide and maintain *in situ* data archives accompanied by collocated satellite data. These activities ensure a data base for the evaluation of existing data sets and new retrievals.

(*vi*) New mission concepts like GPM should be also considered as a valuable contribution to the air-sea flux community. The radiometers planned for GPM are similar to SSM/I or TMI and can be used to derive basic state variables. The relatively dense temporal sampling (3 hourly) would be tremendously useful in the study of ocean-atmosphere fluxes and would contribute towards more uniform error characteristics on the finer spatial/temporal time scale desired for some applications.

(*vii*)The open distribution, preservation and availability of air-sea flux data sets and products has to be ensured to foster international co-operation in the development of improved air-sea flux fields.

7. Acronyms

AMSR	:	Advanced Microwave Scanning Radiometer
AVHRR	:	Advanced Very High Resolution Radiometer
CERSAT	:	Centre ERS-1 d'Archivage et de Traitement
COADS	:	Comprehensive Ocean Atmosphere Data Set
ECMWF	:	European Center for Medium Range Weather Forecasting
ERS	:	European Remote Sensing satellite
GPM	:	Global Precipitation Mission
GSSTF	:	Goddard Satellite-Based Surface Turbulent Fluxes
GTS	:	Global Telecommunication System
HOAPS	:	Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data
J-OFURO	:	Japanese Ocean Flux Data Set with Use of Remote Sensing Observations
NASA	:	(US) National Aeronautics and Space Administration
NCEP	:	(US) National Centers for Environmental Prediction
NOAA	:	(US) National Oceanic and Atmospheric Administration
NSCAT	:	NASA Scatterometer
OWS	:	Ocean Weather Ship
SCOR	:	Scientific Committee for Oceanic Research
SSM/I	:	Special Sensor Microwave/Imager
SST	:	Sea Surface Temperature
SSST	:	Sea Surface Skin Temperature
TMI	:	TRMM Microwave Imager
TRMM	:	Tropical Rainfall Measuring Mission
VOS	:	Voluntary Observing Ship
WCRP	:	World Climate Research Program

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