The relationship between atmospheric Sea Level Pressure (SLP) and the Sea Level Anomaly (SLA) measurements is investigated during storms and very low pressure conditions.

The S- and C-band measurements are used because they are less impacted by rain than the Ku-band. Specific altimeter treatments need to be applied to obtain a relevant along track SSH signal especially during tropical cyclones (SSB and wet troposphere correction). More accurate strong wind speeds have been computed thanks to the Young algorithm.

The ocean signal not related to atmospheric pressure needs to be removed with accuracy thanks to along-track low-pass filtering for extra-tropical depressions (ETD) or by removing the maps of SLA provided by SSALTO/Duacs for tropical cyclones (TC).

Three different SLP-SLA regression models are proposed for north Atlantic, north Pacific and Indian oceans; the error is 5 mbars if compared to ECMWF or buoys SLP.

In order to better understand the SLP-SSH relationship, and the impact of the wind, an analysis of the sea level computed by the MOG2D simulations has been performed.

1. INTRODUCTION

The Inverse Barometer (IB) response has been extensively studied for normal meteorological conditions [1, 14]; but it remained uncertain that there exists a well SLP/SLA correlated signal during storms and hurricanes which are generally characterized by heavy rains, high sea states and strong winds.

This study aimed at investigating the relationship between atmospheric Sea Level Pressure (SLP) and the Sea Level Anomalies (SLA) measurements during storms and very low pressure conditions, in order to retrieve the surface pressure from altimeter measurements. The main issues raised are the problem of the lack of altimeter data due to measurement corruption by rain and to the low accuracy of the different geophysical/instrumental altimetric corrections during TCs, the filtering of the SSH variability not related to atmospheric pressure, the availability of accurate SLP fields, and the definition of the regression models.

We will first describe the database and the methodology used. The fourth and fifth part of the paper present the results obtained for tropical cyclones and for extra-tropical depressions respectively. The last section describes a model based analysis of the SLP-SSH relationship.

2. DATABASE

We have chosen the 2003/2004 time period for the analysis because we benefit from several independent databases:

- the ENVISAT, Topex/Poseidon and Jason-1 altimeter missions;
- the extensive observing network deployed in the Atlantic ocean by NOAA: NHC winds for TCs [9];
- collocated JASON/buoy database: buoy data include the NDBC network, data available via Météo-France, and TAO array;
- the 0.5 degree-6 hours resolution for the ECMWF pressure analysis;
- the QuikScat scatterometer measurements of wind. QuikScat measurements are strongly contaminated by rain, and are unusable for TCs’ study. QuikScat winds are more reliable for ETDs (lower winds); surface pressure fields can also be derived from the QuikScat wind using a Planetary Boundary Layer model (noted PBL; [6]).

ECMWF pressure field is enough accurate for ETDs study thanks to the assimilation of QuikScat data since 2002. On the contrary, these model fields cannot be used for TCs because they are underestimated and mislocalised, due to the coarse space and time resolution of the model and to the model physics.

The Sea Level Anomaly (SLA) derived from altimetry has the following formulation:

\[ SLA = \text{Orbit} - \text{Range} - \text{MSS}_{\text{CLS}} - \sum \text{Corrections} \]

\[ \sum \text{Corrections} = \text{Sea State Bias} + \text{Radiometer wet tropospheric correction} + \text{Ionospheric correction} + \text{GOT2000 ocean tide} + \text{Solid earth tide} + \text{Polar tide}. \]

\[ \text{MSS}_{\text{CLS}} \] is the Mean Sea Surface. IB and dry tropospheric corrections are not applied because they are correlated to SLP.
3. METHODOLOGY

The methodology consists in computing two SLP and SLA storm databases, respectively for TCs and ETDs. Tropical cyclones and Extra tropical storms are treated separately because: ETDs are large scale and very numerous, while TCs are more occasional phenomena occurring in very short distances, with great evolution speeds and particularly severe conditions of wind and rainfalls. In the TC cases, altimetry measurements are found to be severely corrupted.

First step consisted in localizing the extreme events on the NHC or ECMWF databases (resp. for TCs and ETDs), following the criteria:

\[ \text{Wind speed} > 15 \text{ m/s for TCs} \]
\[ \text{DP} = \text{SLP} - \bar{P} < -10 \text{ mbars for ETDs} \]

\( \bar{P} \) is the instantaneous mean global ECMWF SLP. The low pressure event is co-localized with the altimeter measurements.

The second step was to compute the corresponding along-track SLA from altimeters: specific dedicated processing and corrections have been defined for TCs, while the altimeter validated databases can be used for ETDs.

A crucial issue to improve the SLP-SLA correlation, is to remove from the SLA signal the ocean variability not related to atmospheric pressure, ie. the low frequency oceanic variability and the mesoscale variability. For this purpose, several filtering methods have been tested:

- Along-track spatial filtering with low-pass filter: filtering wavelength of 1500km for ETDs;
- Removing SLA maps (MSLA) from SSALTO/Duacs for TCs.

The quantitative impact of the filtering has been evaluated via the computation of SLP-filtered SLA correlations. The best filtering process appeared to be the along track low-pass filter for ETDs. For TCs, the MSLA filtering gives better results due to the small scale of the phenomena and to its rapid evolution; this filtering method is very robust even in a real time processing context.

As the Ku band is corrupted in tropical cyclone cases [10], because of strong attenuation during rain, an expected-Ku band backscatter coefficient \( (\sigma_0) \) has been recomputed from [11], which give the correspondence between Ku and S bands. The Young algorithm [12] and the expected-Ku \( \sigma_0 \) allow computing a new wind speed for values over 20 m/s. This new wind speed is shown on figure 1 for Isabel TC: it is stronger than the ECMWF value and closer to the HRD measurements in the fiercest area of the storm.

Figure 1. Comparison of different wind speed for Jason-1 during ISABEL cyclone.

4. TROPICAL CYCLONES

To investigate the relationship between SLP and SLA during Tropical Cyclones, we have to deal with two main issues: the first issue is the lack of accurate pressure and wind fields measurement during TCs. At the present time, only NHC wind measurements are reliable [9], but they are very occasional and localized. The PBL model is inadequate for TCs and cannot give any pressure signal [6].

The second issue is the lack of validated altimeter data during TCs. Due to their short scale and very high frequency compared to inter track satellite distances and delay, it is statistically unlikely to get a satellite flying over the eye of a hurricane. When it happens, altimeter measurements are severely affected: measurements are corrupted by rain and the different geophysical/instrumental altimetric corrections used are not accurate enough for extreme weather.

Specific altimeter data processing is needed in order to improve the capability of altimetry to observe TCs. The problem of rain contamination is partly fixed using C or S-band measurements on Jason 1 and Envisat respectively; these bands are less affected by rain than the Ku one, but they are also noisier. SSB and wet Troposphere correction need to be recalculated in this extreme weather specific context.

Computation of \( \sigma_0 \) and Wind Speed

As the Ku band is corrupted in tropical cyclone cases [10], because of strong attenuation during rain, an expected-Ku band backscatter coefficient \( (\sigma_0) \) has been recomputed from [11], which give the correspondence between Ku and S bands. The Young algorithm [12] and the expected-Ku \( \sigma_0 \) allow computing a new wind speed for values over 20 m/s. This new wind speed is shown on figure 1 for Isabel TC: it is stronger than the ECMWF value and closer to the HRD measurements in the fiercest area of the storm.

Figure 1. Comparison of different wind speed for Jason-1 during ISABEL cyclone.
The neural wet troposphere correction used for Envisat data is very noisy and it is not formulated for high sea state conditions. The ECMWF correction is underestimated in such extreme conditions and cannot be used. The initial parametric formula used for Envisat in the GDRs gives very strong values of the wet troposphere correction because of heavy rain and high wind speed (black curve on figure 2).

A new parametric formula has been computed when including in the learning data base, the altimeter winds greater than 25 m/s. It gives:

\[ \text{Wet}_{\text{tropo}}^{\text{Extreme}} = 62.1360 - 58.1935 \times \log(280 - TB^{23.8}) + 48.1591 \times \log(280 - TB^{36.5}) - 0.236073 \times (\text{WindSpeed} - 7) \]

The wind speed is in m/s. The brightness temperatures (TB) are in K and the resulting correction is in mm.

The new correction (red curve) has weaker values during TCs but it is not adapted for lower wind speed around the area of the TCs. The two corrections need to be combined in a composite correction (blue curve): if initial correction is greater than 0.5 m (which is the threshold for normal sea state conditions), the recomputed wet tropospheric correction is taken. A final smoothing allows avoiding any discontinuities between the two corrections.

The new SSB is very close to the NP SSB for values of 6m SWH and 20m/s wind speed, which shows the continuity between the different SSB values in normal and extreme meteorological conditions.

### Filtering of SLA for TCs

The MSLA filtering allows removing ocean signal not related to atmospheric pressure with good accuracy during TCs. Several SLA maps have been computed in order to improve the filtered signal: an optimal interpolation (OI, [15]) using the complete data set with a window of 40 days or removing spatial and temporal areas corresponding to the cyclone. A correlation analysis between SLA-MSLA and SLP has shown closed results for the different mapping, confirming the robustness of this filtering method.

Note that the MSLA filtering has been tested in a Near Real Time (NRT) context, using in the OI only the last available measurements before the day of the cyclone: results are very similar to the off-line MSLAs and show the efficiency of the method and the ability of NRT altimetry to detect such extreme events.

Figure 3 shows the reconstructed signal (SLA-MSLA) using all new dedicated processing (SSB, Wet troposphere) for Isabel TC.

### SSB Estimation

A new SSB estimation has been computed in S-band for Envisat. A one year crossover database set with dedicated processing and wind speed>15m/s has been computed. Estimating a Non Parametric SSB [4] on such dataset is very close to fitting a BM1 usual model (SSB=A*SWH), which gives:

\[ \text{New SSB} = -6\% \times \text{SWH} \] (5)

The SLP field can be retrieved from the QuikScat winds, thanks to the use of a PBL model [6]. A reanalysis of the ECMWF surface pressure fields has been performed to produce one single SLP reference data-set, merging ECMWF and QuikScat data in order to improve the storm structures, location and intensity. The merging method is the one already employed by [2], to create merged NCEP/QuikScat wind fields. It is based upon a wavelet analysis that splits the field into different components representative of different variability
scales. This is done separately for ECMWF and QuikScat and a merged SLP field can then be reconstructed by adding both contributions for the desired space variability scales. Figure 4 presents the resulting merged SLP field. The entire QuikScat time period has been processed to produce this ECMWF re-analysed fields covering July 1999 until June 2005. This new collocated SLP database will help validating the altimeter-based pressure field.

Figure 4: ECMWF (top panel), QuikScat (bottom panel), and merged (middle panel) SLP fields.

**SLP-SLA Regression Analysis**

A and B regression coefficients (from eq. 3) have been fitted through a least square method, focusing on the fiercest area of the storm. Best correlations between SLP and SLA have been obtained when excluding coastal areas and strong mesoscale variability areas from the analysis. The analysis has been performed for three different oceans: the regression models obtained for the north Atlantic, north Pacific and the Indian Oceans are given in Table 2. Note that the correlation between SLP and SLA is strong. The value of A is different from an IB, due to strong wind effects; note that A < IB in absolute value, because the dry tropospheric correction has not been applied on the SLA. A is greater in absolute value in the Indian Ocean likely due to stronger ETDs. The rms of the restitution error, if compared to ECMWF SLP, is 5.2 mbars for the three oceans.

<table>
<thead>
<tr>
<th>ocean</th>
<th>A (mbar/cm)</th>
<th>B (mbars)</th>
<th>Correlation</th>
<th>Error on 2004 rms/mean (mbars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Atlantic</td>
<td>-0.796</td>
<td>-172.89</td>
<td>-0.83</td>
<td>5.25/-0.4</td>
</tr>
<tr>
<td>North Pacific</td>
<td>-0.77</td>
<td>-173</td>
<td>-0.84</td>
<td>5.2/-0.3</td>
</tr>
<tr>
<td>Indian</td>
<td>-0.817</td>
<td>-175.35</td>
<td>-0.88</td>
<td>5.16/-1.2</td>
</tr>
</tbody>
</table>

Table 2: SLP-SLA regression models for 2003 extra-tropical depressions.

**Validation**

Complementary validations of the altimeter restored SLP have been performed with independent datasets: QuikScat SLP and the collocated JASON/buoy product are both available at IFREMER. Only off shore buoys with an estimated local pressure difference greater than 10 mbars have been used for the validation: it remains 162 collocated data.

Table 3 presents some Jason-QuikScat and the Jason-ECMWF statistical comparisons: the mean correlation is close to 0.95, whatever the ocean basin. The percentage of correlation lower than 0.8 is close to 10, with significantly lower values in the northern hemisphere. This difference between northern and southern hemisphere is likely due to the large ACC strong variability area which may pollute the pressure induced SLA signal in southern hemisphere.

<table>
<thead>
<tr>
<th></th>
<th>N.Atlantic</th>
<th>N.Pacific</th>
<th>Indian</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean correlation coefficient</td>
<td>0.96</td>
<td>0.95</td>
<td>0.96</td>
</tr>
<tr>
<td>% of correlation coefficient &lt; .8</td>
<td>6.7</td>
<td>8.5</td>
<td>11.8</td>
</tr>
</tbody>
</table>

Table 3: Mean correlation coefficient between the SLP, and percentage of cases for which this correlation is lower than 0.8, for each ocean basin. The first value is for the Jason/QSCAT correlation, the second for Jason/ECMWF

When the ETDs are strong and large scale if compared to the background variability, altimetry allows restoring an accurate pressure signal (figure 5). But error can be greater for smaller scale ETDs which might be smoothed out by the large scale along-track filtering, and due to strong and localised wind effects which are not taken into account within the basin-wide mean regressions.
Figure 5: comparison of the along-track SLP for the ETD of 23/04/2004 21:08 UTC QuikScat time.

Figure 6 shows the comparison of the Jason SLP with buoys measurements. As expected, the Jason SLP is systematically underestimated (bias of 3 mbars); the rms error between Jason and buoys SLP is only 5 mbars. There is a small residual dependency of the error (Jason–buoy SLP) on the sea level anomaly, which means that the regression models could still be improved.

Figure 6: Comparison of the Jason SLP with buoys measurements (abscissa). The coloured bar gives the SLA.

6. DYNAMICAL MODELLING APPROACH

We propose to use MOG2D simulations to investigate further the SLP-SSH relation during mid-latitude storms. MOG2D is a finite elements non-linear gravity waves model using shallow water equations. This global barotropic model allows simulating the high frequency response of the ocean to atmospheric pressure and wind forcing [1, 3]. The model is forced by ECMWF pressure and wind fields. MOG2D outputs contain in essence, only atmospherically forced signals; if neglecting model errors, model sea level thus represents the ideal along track filtering and the ideal altimeter measurement of the SLA signal.

SLP/MOG2D Sea Level Regression Analysis

The mean regression between MOG2D sea level and the ECMWF SLP has been performed on all 2003 off-shore ETDs (table 4). Note that the MOG2D sea level does not need to be along-track filtered as it is, in essence, only representative of the ocean response to atmospheric wind and pressure forcing.

<table>
<thead>
<tr>
<th>Ocean</th>
<th>A (mbar/cm)</th>
<th>B (mbars)</th>
<th>Correlation</th>
<th>Error on 2004 (mbars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Atlantic</td>
<td>-1.13</td>
<td>-2.7</td>
<td>-0.91</td>
<td>3.57/-0.34</td>
</tr>
<tr>
<td>North Pacific</td>
<td>-1.07</td>
<td>-0.95</td>
<td>-0.94</td>
<td>3.45/0.15</td>
</tr>
<tr>
<td>Indian</td>
<td>-1.2</td>
<td>-4.66</td>
<td>-0.87</td>
<td>4.77/-0.81</td>
</tr>
</tbody>
</table>

Table 4: SLP-MOG2D Sea level regression models for 2003 extra-tropical depressions.

As expected, the linear regression coefficient A is greater than 1 mbar/cm in absolute value, traducing the anticorrelation between the pressure and the wind effects. The global error on the restituted pressure is significantly weaker when considering MOG2D signal instead of altimeter measurements (table 2): the improvement reaches more than 30 % for north Atlantic and north Pacific oceans. This residual error is due to model errors and to the limitation of the global linear regression model; it represents the minimum gain we could get on the altimeter based regression models, while improving the filtering of altimeter data from all signals not related to atmospheric forcing. Note that a multivariate regression analyses between SLP, MOG2D sea level and altimeter wind speed, did not allow improving significantly the performances of the regression model.

Regional Variability of the SLP-SLA Relation

The spatial variability of the SLP-MOG2D sea level relation has been investigated: regression and correlation maps have been computed for north Atlantic, north Pacific and Indian Oceans. As expected, the correlation and the regression coefficients have a strong spatial variability [8]: the correlation is smaller and A is smaller in absolute value, in coastal areas, due to non linearities, dissipation, and coastal wind effects [4]. The correlation between SLP and SSH is also smaller in deep ocean regions where the ocean has a strong dynamic response to wind forcing [1, 13]; in these regions, A is greater in absolute value, due to the anticorrelation between the wind and pressure effects [7].

The absolute value of the regression coefficient is the highest in the Indian Ocean (figure 8), where the ocean is known to have a resonant response to wind forcing south-west of Australia [13].

Note that using the regional regression models instead of the basin wide ones allows getting closer to QuikScat SLP.
Figure 8: regression coefficient A between SLP and MOG2D sea level in the Indian ocean. Scale= [-1.6..-0.8 mbars/cm].

7. CONCLUSIONS

The SLA altimeter measurements during TCs have been improved: dedicated altimeter processing using S or C band, specific SSB and wet tropospheric corrections have been proposed. A more accurate wind speed has been computed for extreme winds. For TCs, the MSLA filtering is very efficient to extract the atmospherically forced signal even in a NRT context, showing the ability of altimetry to detect such extreme events. However, the retrieval of surface pressure from altimetry during TCs was not possible due to the poor quality of the pressure data sets.

A complete Pressure-Wind database during ETDs and derived from QuikScat data has been computed on the 1999-2005 period.

The altimetry allows restoring a pressure signal during extra-tropical storms with good correlation between SLP and SLA (>0.8). The regression model error is about 5 mbars. Strong mesoscale variability areas are a strong error source when restoring the pressure signal from altimetry. Moreover the strong and localised effects of intense wind forcing are difficult to take into account in the global regression model.

MOG2D dynamical approach allowed pointing out the importance of the spatial variability of the regression models. The mean regression model based on MOG2D outputs have a 3 mbars error, likely due to ECMWF forcing errors, model errors and the use of a global regression model instead of a regional one.

8. REFERENCES

8. Ponte and Gaspar 1999: Regional analysis of the inverted barometer effect over the global ocean using T/P data and model results, JGR, 104 (C7).

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