**Introduction and aims**

We analyze the errors that are inevitably associated to hydrodynamic models, in a realistic case. The error of the GHER model in the Mediterranean Sea has already been studied in e.g. Beckers et al. (2000) by comparing it with other primitive equation models, or in Alvera (2004) by comparing the model with observations and with the climatology, using usual statistical methods and also wavelet decompositions. In this study, we rather study the sensitivity of the model to various variables using an ensemble of models. We chose a relatively high resolution, 1/16°, corresponding to the resolution now used in operational OGCMs covering the Mediterranean, such as the MFS system (http://www.bo.ingv.it/mfs). 

**Ensemble generation**

We generated 6 sub-ensembles by considering: 

i. *bathmetry* uncertainties (6 members obtained by more or less smoothing of the original bathymetry)  
ii. *air temperature* uncertainties (60 members generated by randomly modifying the weights in a principal component analysis of the field)  
iii. *cloud coverage* uncertainties (60 members, idem)  
iv. *wind velocity* uncertainties (60 members, idem)  
v. *horizontal diffusion coefficient* uncertainties (4)  
vi. *initial conditions* uncertainties (60 members by random initial fields modification in the Fourier space)  

This ensemble of 250 members is then evolved in time with the GHER model during a 1-month simulation. The statistics calculated on the ensemble are, in fact, the response of the non-linear hydrodynamic system to errors on the forcing terms. We calculate (a) the temporal evolution of the rms error and the temporal "stability" of this error, (b) the spatial patterns of the error: 1st to 4th order moments of this error, and its principal components, called EOFs (not shown here).  

**Results and conclusions**

The time evolution of the root mean square error in the different sub-ensembles is given in the graphic below, for temperature and surface elevation.  

![Graph showing the time evolution of the root mean square error](image) 

It appears that:  

- wrong atmospheric forcings yield increasing errors with time  
- using realistic perturbations in all sub-ensembles, it appeared that the air temperature and wind uncertainties cause the largest oceanic errors  
- bathymetric errors or smoothing lead to errors in small areas  
- bad diffusion parameters lead to constantly increasing errors  
- Too large diffusion is worse than too small diffusion  

The mean of each sub-ensemble is always close to the reference member, a desirable property. However some spatial structures appear. Bathymetry uncertainties lead to increased errors where large topographic gradients exist (continental shelf breaks, wells, Greek islands etc.). The wind causes surface elevation errors, mainly in shallow areas. Later, errors accumulate along the coastlines. The cloud field or diffusion errors do not yield particular spatial structures. The initial condition uncertainties yield errors of the same kind, which slowly are attenuated with time.

The variance plots in each sub-ensemble indicate the location of areas with the largest dynamical response to perturbations.  

![Variance plots](image)  

Plots are typical for the corresponding perturbations,  

- bathymetric errors cause variability above them  
- wind errors cause variability in various areas, as well as in general in the South of the Western Basin. They might attenuate or reinforce gyres  
- errors on diffusion coefficients, initial conditions and air temperature also lead to patched std.dev. errors corresponding to areas of intrinsic higher variability  
- cloud coverage perturbations yield almost uniform variance maps  

Skewness (3rd moment) and kurtosis (4th moment) indicate if the PDF of the error can be considered Gaussian or not. It appears that the error processes are mostly Gaussian, with some exceptions. E.g. the skewness is usually zero on average, but where the bathymetry is modified, the skewness is systematically negative. Thus, it leads to non-Gaussian error distributions! 

**Applications**

- The model error is interesting as such: we now quantitatively know how various errors or uncertainties affect model results.  
- However, it can also be used for different purposes. For example, it allows using data assimilation techniques without needing the usual assumptions of Kalman-derived filters.  
- It also allows studying the sensitivity of coupled models (biological, oil spill, search-and-rescue …) to physical forcings.

**References**