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Identification of high tide models in the Venetian lagoon: variable selection and G-LASSO ⋆

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Abstract: The objective of this paper is to investigate the performance of statistical models to predict high tide events in the Venetian lagoon. Some exceptional high tide events are analyzed and various refinement of the models, for prediction of high tide events, are presented. The relevance of the external inputs, in particular of the meteorological agents, is tested via a Group-LASSO technique.
Keywords: Time series modeling, Stochastic system identification, Estimation and filtering, Variable selection, Group-LASSO, Tide prediction.

1. INTRODUCTION

High tides are a source of major concern for the city of Venice. Conventionally a tide is classified as high ("acqua alta" in italian), if the sea level at *Punta della Salute*, which is an hydrographic station situated at the outlet of the Grand Canal, reaches 80 cm. This level corresponds to flooding of the lowest sides of the town (St. Mark's Square). The alarm to the population is given when the tide is about to reach 110 cm. When the water level exceeds 140 cm the high tide is classified as exceptional and more than 60% of the city is flooded. Historically, exceptional high tides were very rare; for example only 8 events were registered between 1950 and 2000. However, lately their frequency is increasing: 6 such events were registered between 2000 and 2010 and 3 events occurred just in 2012. This increase is due to phenomena such as eustatism (sea level rise) and subsidence (lowering of the soil). To protect the city of Venice, a system of mobile barriers at the three main inlets of the lagoon (the "Mose") is under construction. To efficiently control it, an accurate prediction of the tide level is needed from 3 to 12 hours ahead, requiring the development of very precise models of the tide. The first class of models developed were physical/ hydrodynamical models of water flows in and around the lagoon, see e.g. [Bargagli et al. 2002, Fagherazzi et al. 2005, Carniello et al. 2005, D'Alpaos and Defina 2007, Lovato et al. 2010, Bertotti et al. 2011b]. Lately, however, the general tendency is to employ statistical models, which do not require the modeling of the extremely complicated system of canals and marshes surrounding the city. The model currently in use, called EXCO2, belongs to this second class, although some of the relevant pressure data are refined via a physical model, and has been operational since 1993 [Vieira et al. 1993]. EXCO2 is an ARX model which uses as exogenous variables the pressures in four key geographical locations: Alghero, Genova, Venice and Bari, together with five squared pressure gradients across the Adriatic, namely along the joints Trieste-Ravenna, Pula-Rimini, Zadar-Pescara, Split-Termoli, Dubrovnik-Bari, which are used to estimate the wind effect, see Fig. 1.

The use of ARX structure for modeling the tide phenomenon has been statistically validated in [Parise and Picci 2013]. One of the main results therein was that the set of inputs currently in use can be improved. In particular it was shown that the use of wind velocity and direction in four key stations, namely Venice, Trieste, Bari and Dubrovnik, as additional inputs, leads to better performance for the prediction from 3 to 10 hours ahead. These results refer to the behavior of models identified using the whole dataset, which mainly contains normal tide levels, that is, levels way under the threshold of 110 cm. The main objective of this paper is to test whether these results are valid also for the particular conditions associated to high tide events. These events are indeed rare and their contribution to average indices such as the normalized mean square error (NMSE), is negligible. This analysis could hopefully give a better insight on the validity of the models and suggest ways to improve them. The crucial question of input selection is also addressed: in the literature the choice of inputs is usually justified by physical motivations but it is far from clear whether all the used inputs are necessary or if there is some redundancy. In this paper we compare the predictions obtained by using input sets selected on the basis of experience with the performance of models identified using variable selection criteria, like the Group-LASSO [Yuan and Lin 2006].

The paper is organized as follows: Section 2 describes the available dataset. In Section 3 the ARX structure and a first analysis of the model behavior during high tide events is presented. In Section 4 the exceptional high tide event of 31^{th} October 2012 is analyzed. A model refinement for high tide events in presented in Section 5. In Section 6 optimal input selection problem is discussed. Section 7 concludes the paper.

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2. THE DATA

The tide is the sum of an astronomical component and a meteorological one. The former is totally predictable, therefore in the following, we shall only deal with the latter (obtained as actual water level minus the astronomical component). The Adriatic basin behaves like a cavity oscillator: following an initial perturbation, pronounced free oscillations called *seiche* (*sessa* in italian) are clearly visible with an approximate period of 21-22 hrs. Seiche waves are very lightly damped and added to the astronomical component can lead to high tides even days after the initial perturbation. Apart from this phenomenon, the main external agents influencing the meteorological tide are pressure and winds, as stated by [Vieira et al. 1993]. The European Centre for Medium-Range Weather Forecasts (ECMWF) in the UK can provide daily predictions of these data for 180 hours ahead, with a three hours period. Fig 1 indicates the location of the available predicted data. Measured data of wind were also available at Piattaforma CNR (Venice) and Grado (near Trieste). For model calibration

Fig. 1. Available data: pressure (white), pressure and winds (light blue) and pressure gradients (black lines).

(identification) historical hourly sea level measurements at the *Punta della Salute* hydrometer from 7/05/2009 to 31/01/2011 = 14,967 are used. For the validation of the models the data from 01/09/2012 to 31/12/2012 are used, for a total of 2,928 measurements. Note that this period corresponds to autumn-winter months, i.e. when the meteorological component is more relevant, and includes the 3 exceptional high tide events registered in 2012.

3. THE MODEL

The model structure considered in this paper is of the ARX type, the same of the existing model EXCO2. An ARX model has the form

$$y(t)=c+\sum_{i=1}^{n} a_i y(t-i)+\sum_{j=1}^{M}\sum_{i=1}^{m_j} b_{j,i} u_j(t-k_j-i+1)+\epsilon(t), \quad (1)$$

where $y(t)$ is the meteorological tide while $u_1(t), ..., u_M(t)$ are the M inputs of the system, that is external signals as pressure and wind. The constant c is an offset due to the fact that the signals $y(t)$ and $u(t)$ have non-zero mean. In the following we will use the notation $A = [a_1, ..., a_n]$ and $B = [B_1, ..., B_M]$, where $B_j = [b_{j,1}, ..., b_{j,m_j}]$.
For identification, the data need to be detrended by subtracting the sample means of $u(t)$ and $y(t)$, moreover for the purpose of Section 6 the inputs need to be normalized to unitary variance. The means and variances are first estimated from the identification data and then subtracted from the actual input-output signals to get

$$y'(t) = y(t) - \hat{\mu}_y, \quad u'_j(t) = \frac{u_j(t)-\hat{\mu}_{u_j}}{\hat{\sigma}_{u_j}} \quad j : 1, ..., M,$$

which are used to estimate a detrended model

$$y'(t) = \sum_{i=1}^{n} \hat{a}_i y'(t-i) + \sum_{j=1}^{M}\sum_{i=1}^{m_j} \hat{b}_{j,i} u'_j(t-k_j-i+1) + \epsilon(t). \quad (2)$$

The offset is then computed by substitution

$$\hat{c} = \hat{\mu}_y \left(1 - \sum_{i=1}^{n} \hat{a}_i\right) - \sum_{j=1}^{M}\sum_{i=1}^{m_j} \frac{\hat{b}_{j,i}}{\hat{\sigma}_{u_j}} \hat{\mu}_{u_j}, \quad (3)$$

getting

$$y(t) = \hat{c} + \sum_{i=1}^{n} \hat{a}_i y(t-i) + \sum_{j=1}^{M}\sum_{i=1}^{m_j} \frac{\hat{b}_{j,i}}{\hat{\sigma}_{u_j}} u_j(t-k_j-i+1) + \epsilon(t). \quad (4)$$

The structure indices $n = 33$, $m_j = 13$ and $k_j = 1$ for all j, are used. These indices are used by the current model EXCO2 and it was shown in [Parise and Picci 2013] that they lead to a statistically consistent model and that, selecting different orders m_j and k_j, within a rather wide range, does not improve the performance. The identification of the parameter vector $\theta = [a_1, \dots, a_n, b_{1,1}, \dots, b_{M,m_M}]$ is done by minimizing the one-step ahead prediction error $e_\theta(t) = y(t) - \hat{y}_\theta(t|t-1)$ (PEM), that is

$$\hat{\theta} = \min_\theta V(\theta), \quad V(\theta) = \frac{1}{N_{id}} \sum_{i=1}^{N_{id}} ||y(t_i) - \hat{y}_\theta(t_i|t_i-1)||^2. \quad (5)$$

Under Gaussian assumptions this estimator is known to be asymptotically equivalent to the Maximum Likelihood estimator which is consistent and has the smallest asymptotic variance [Ljung 1999].
Using the dataset described in Section 2, we identified two ARX models. The first one, arxA, mimics the structure of EXCO2 while the second one, arxB, uses the new set of inputs proposed in [Parise and Picci 2013], see also Table 1. A third model, arxC, was also identified using true measured data of wind in Venice and Grado [1], instead of the wind predictions from ECMWF. Indeed the wind predictions issued by ECMWF may be quite inaccurate during the highest peaks of a storm, that is during the events of interest [Cavaleri and Bertotti 2006, Bertotti and Cavaleri 2009]. The comparison between arxB and arxC should detect whether the errors in the prediction are due to model mismatch or rather to errors in the inputs. For

Table 1. Nomenclature associated with the different identification datasets

Name	Inputs
$\mathcal{A}$	stand = 4 pressures and 5 square pressure gradients
$\mathcal{B}$	stand + predicted $wind \cdot \lvert wind \rvert$ at Ve, Tr, Ba, Du
$\mathcal{C}$	stand + predicted $wind \cdot \lvert wind \rvert$ at Ba, Du and measured ones at Ve, Gr

the models in the datasets of Table 1 we first proceed to verify whether the results obtained in normal conditions are also valid during high tide events. To this end, the

[1] The measured data of wind at Grado are used instead of those in Trieste since these were not available.

validation dataset introduced in Section 2 is used. Fig. 2 shows the probability density function (pdf) of the one-step-ahead residual prediction errors for the model arxB. Similar results can be obtained with the models arxA and arxC. In the left plot the pdf estimated considering all the validation dataset is shown, while, in the right one, the pdf conditioned on $y(t) > 45$ cm, i.e. high tide events, is shown. While for the complete dataset the residuals look reasonably Gaussian, indicating that a linear ARX model is statistically correct, the pdf estimated on high tide data only, shows a slight multimodality suggesting that some small non-linear effect may be present. Also the shape of the density function looks quite different, a possible indication of non-stationarity.

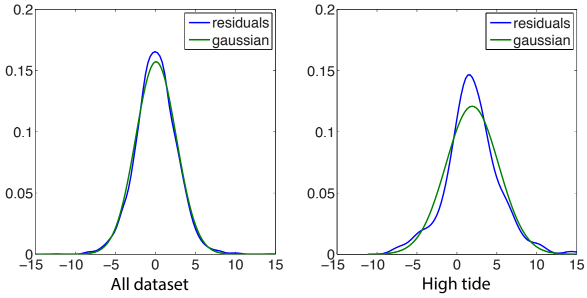

Fig. 2. Distribution of the residuals of model arxB using the whole dataset (left) and only errors for meteorological tide levels over 45 cm (right).

4. ANALYSIS OF AN EVENT OF EXCEPTIONAL HIGH TIDE

The exceptional high tide occurred during the night of October 31^{st} 2012 is a particularly interesting case because for this event, the predictions made with the models currently in use were significantly wrong leading to high exposure in the media.

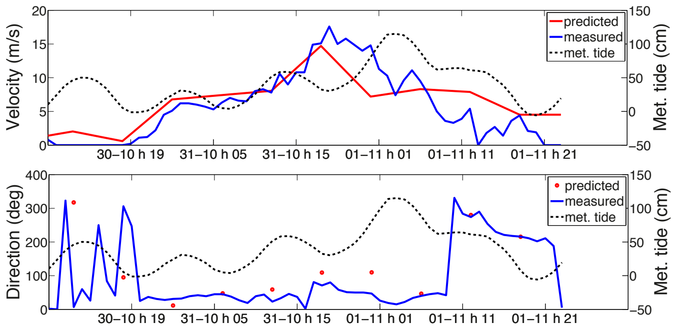

Fig. 3. Comparison of the meteorological tide and the measured/predicted wind in Venice (Piattaforma CNR) for the exceptional tide of October 31^{th} 2012.

4.1 Analysis of the event

Fig. 3 shows the relation between the water level and the wind direction/velocity in Venice during the night of October 31^{th}. It can be seen that:

(1) at the beginning of the period the wind velocity is almost zero and the tide follows the natural sessa oscillation;
(2) from the morning of 31/10 a "Bora" wind with a direction of 50 degs (from NE) starts to flow and reaches its maximum velocity between 7.00 pm and midnight. During the same period the tide level grows and reaches its maximum at 2.00 am;
(3) afterwards the wind velocity decreases and the direction suddenly changes. In this second phase the wind is blowing from 250-300 deg (W) and its effect is to empty the lagoon. Simultaneously the tide level decreases rapidly and the second peak (due to the sessa) does not occur.

Summing up, the analysis of this particular event shows that there is a high correlation between the measured wind in Venice and the tide level. Fig. 3 also shows the comparison between the measured wind velocity and direction in Venice and the predictions issued by ECMWF. It is important to notice that the velocity peak is considerably underestimated by the ECMWF prediction. This is in line with the results reported in [Cavaleri et al. 2010] and in [Bertotti et al. 2011a] where other events of high tide, caused by intense Scirocco wind (SE), are considered. In that case a correction factor between 1.2 and 1.5 was used to compensate for the underestimation of the wind velocity by ECMWF (see Table I therein).

4.2 On-line predictions

In the following with the term *on-line prediction initialized at time t with horizon T* we denote the tide prediction for the interval $t, ..., t+T$ given the measurements up to time $t-1$. To simulate the on-line predictions for the event of October 31^{th}, the standard model arxA, and the two models with wind inputs have been used, see Fig. 4.

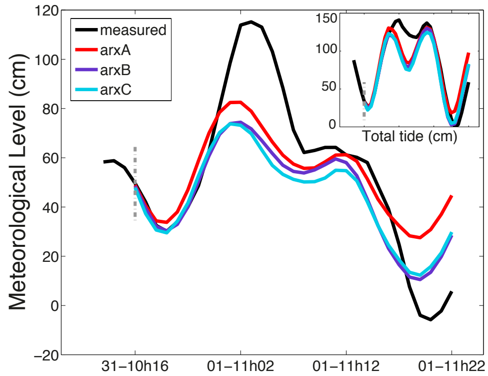

Fig. 4. On-line predictions obtained with the models of Section 3 for the event of October 31^{th} 2012. The simulations have been initialized 12 hours before the peak (vertical grey line).

Surprisingly, the models with wind inputs do not behave better than the standard model, even though the previous analysis has shown a clear correlation between the tide and the wind in Venice. One possible explanation is that the effect of wind inputs is relevant only during high tide events, which are very rare and an identification which uses long data collected in prevalently normal conditions, may provide wind coefficients estimates which are unrealisitically small.

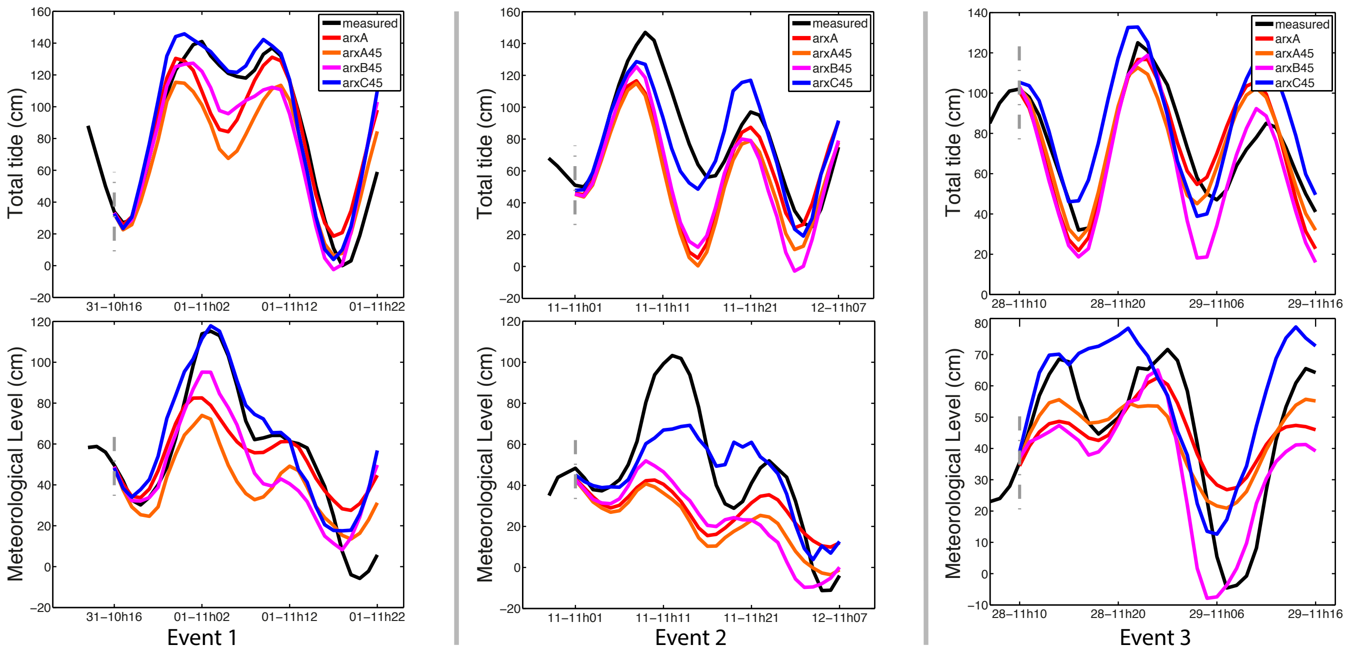

Fig. 5. On-line predictions obtained with the models of Section 5 for the three events of exceptional high tide present in the validation dataset. The simulations have been initialized 12 hours before the peak (grey line).

5. SYSTEM IDENTIFICATION FOR HIGH TIDE EVENTS

In order to confirm the conjecture that the wind coefficients relative to high tide events are underestimated, a new set of models is identified using only data collected during high tide events. A new cost function

$$V_s(\theta) = \sum_{t_i|y(t_i)>s} ||y(t_i) - \hat{y}_\theta(t_i|t_i-1)||^2, \qquad (6)$$

is used for this identification. The main difference with the standard PEM cost function (5) is that only errors relative to meteorological tide above some threshold, $y(t) > s$, are weighted. In the following this threshold is set to 45 cm. Since it is reasonable to assume that the autoregressive dynamics, describing say the "sessa" oscillations, should not be influenced by the weather conditions, only the B matrix is estimated, while the A matrix is fixed to the optimal value found using the whole identification dataset. Fig. 5 shows the on-line predictions obtained with these new models for the 3 events of exceptional tide present in the validation dataset. For each event the on-line predictions of the meteorological and total tide are shown. Looking at the left plots, relative to the event analyzed in Section 4, it is clear that the models using the wind, identified using only high tide events data, arxB45 and arxC45, behave much better than the standard models, arxA, arxB and arxC. It is interesting to notice that they behave much better also with respect to arxA45, which is a model using the standard inputs (no wind) but identified using high tide events data only. There is a clear evidence that the inputs currently in use by EXCO2 are not sufficient to explain high tide events, even with the refinement given by (6). Moreover, between the two models with wind inputs, the one using measured data, arxC45, behaves better than arxB45, which uses predicted data from ECMWF. This is to be expected since, as discussed before, the wind data provided by ECMWF underestimate the real wind velocity, causing errors both in the identification and in the simulation step. In the other two exceptional high tide events the wind effect is still present, hence arxC45 still provides the best performance. Unfortunately this is not sufficient to fully explain these two high tide events. A more detailed analysis, as the one done in Section 4.1 for Event 1, could help to understand other causes of high tide and is postponed to future work. An immediate observation is, however, that for Event 2 and 3 the meteorological peak is less important than in Event 1; the exceptional tide in these events was due to the fact that the peak of meteorological and astronomical tide were in phase. This could indicate that the conditions leading to high tide were different in the 3 events and that the winds alone cannot explain all phenomena. In particular from this analysis it seems that the wind at Venice and Trieste are particularly important to explain events like Event 1 but they do not provide a full picture for Events 2 and 3.

6. REDUCED MODELS AND INPUT SELECTION

In this section we address the question whether all the inputs used by model arxC45 are necessary or if there is some redundancy. Too many inputs and hence too many parameters to estimate may indeed lead to an insensitive error functional and to parameter estimates which are non-robust to perturbations. Related legitimate questions are:

(1) *are the pressure gradients still needed if we include the winds as input?* The reason for introducing them was to take into account the wind effect at geostrophic altitude. However this can become irrelevant if we have now wind data at sea level;
(2) *are all the wind data useful or only those that are closer to the lagoon?* Indeed it could be that the effect of wind on the sea level is important only in the proximity of the lagoon, hence at Venice and Grado (or Trieste), while the effect of the winds at Bari and

Dubrovnik could be taken into account using only the pressure gradients.

To answer these questions the three input datasets D, E and F, reported in Table 2, have been constructed.

Table 2. Identification datasets constructed to answer Questions 1 and 2

Name	Inputs	Quest.
$\mathcal{D}$	4 pressures + predicted $wind \cdot \lvert wind \rvert$ at Ba, Du and measured ones at Ve, Gr	(1)
$\mathcal{E}$	stand + measured $wind \cdot \lvert wind \rvert$ at Ve, Gr	(2)
$\mathcal{F}$	4 pressures + 3 pressure gradients at T-R, Z-P, D-B + predicted $wind \cdot \lvert wind \rvert$ at Ba, Du and measured $wind \cdot \lvert wind \rvert$ at Ve, Gr	(1)

This problem can be also addressed in an automated way, without reference to the physical meaning of the input variables. The so-called Group-LASSO method [Yuan and Lin 2006] for variable selection sets automatically to zero the coefficients of the less relevant inputs. The method uses a modified cost function like

$$V_{\lambda,s}(\theta) = V_s(\theta) + \lambda \textstyle\sum_{j=1}^{M} ||B_j||, \qquad (7)$$

which is the sum of the original cost function (6) plus a term that penalizes the sum of the 2-norm of the coefficient vector of each input. Note that the 2-norm of this vector is proportional to the importance of the corresponding input since the input data have been normalized to (zero mean and) unit standard deviation. The parameter λ tunes the relative importance between high accuracy in prediction and number of inputs. The optimal value of this parameter can be chosen by cross validation.

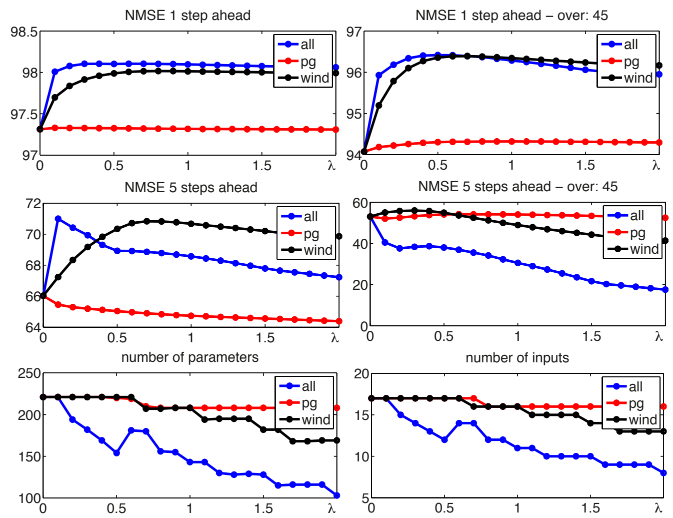

Fig. 6. Relation between λ and the NMSE using all the validation dataset (left column) or only high tide events (right). In the bottom line the number of parameters and the selected inputs ares reported.

Fig. 6 shows the normalized mean square error (NMSE) obtained in validation,

$$NMSE(\theta) = 100\left(1 - \frac{\sum_{i=1}^{N_v} ||y(t_i) - \hat{y}_\theta(t_i|t_i-1)||^2}{\sum_{i=1}^{N_v} ||y(t_i) - \frac{1}{N_v}\sum_{i=1}^{N_v} y(t_i)||^2}\right),$$

for models identified using different values of λ and the corresponding number of inputs. The cost function (7) was used to estimate the coefficients of all inputs, "*all*", but also to refine only some of the coefficients of arxC45. In particular to answer Question 1 it has been chosen to estimate only the coefficient of the squared pressure gradients, "*pg*", fixing all the others to the values of arxC45. To answer Question 2, on the other hand, only the coefficients of the wind have been used as free parameters, "*wind*". In Fig. 6 it is shown the NMSE using all the residuals but also using only the ones corresponding to high tide events. Table 3 reports which inputs are set to zero by this identification procedure for λ up to 0.5 for "*all*" and 1.5 for "*wind*" and "*pg*", since for values greater than these the performance is decreasing.

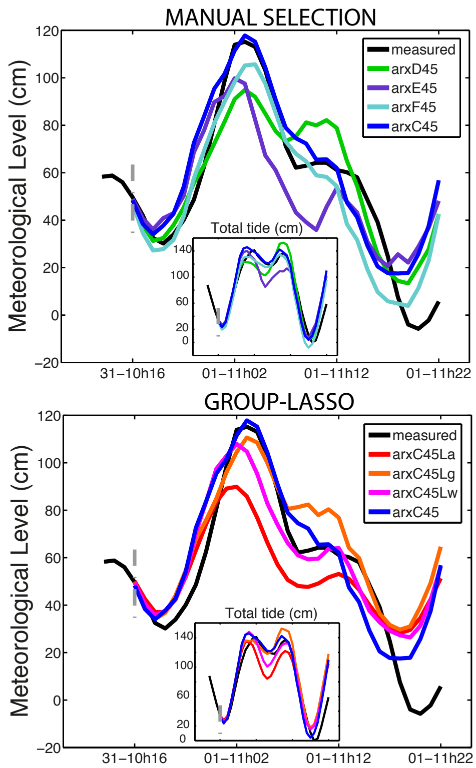

Fig. 7. On-line predictions of the models in Section 6, initialized 12 hours before the peak (vertical grey line), for the exceptional tide of October 31^{th} 2012.

Finally Fig. 7 shows the on-line prediction for Event 1 obtained using the models identified from the intuitively planned datasets D, E and F, and the models identified from dataset C using Group-LASSO with the values of λ that maximizes the 1-step-ahead NMSE for high tides for the three different sets of free parameters, see also Table 4. In all cases a threshold of 45 cm has been used for $V_s(\theta)$. Looking at the top plot it is evident that the answer to Question 1 is negative. In fact the model arxD45 (green), that does not use any pressure gradient, behaves much worse than arxC45 (blue). Using 3 pressure gradients the prediction improves, arxF45 (light blue), but is still worse than using all of them. Moreover removing the winds in Bari and Dubrovnik, as proposed in Question 2, leads to the worst performance, arxE45 (purple). The removal of only some of the pressure gradients, arxC45Lg (orange), or only some of the wind data, arxC45Lw (pink), using Group-LASSO, on the other hand, leads to better results, even though the model with all the inputs is still preferable. Finally, note that using the Group-LASSO technique to choose between all the inputs, arxC45La (red), is not a valid option. This could be due to the fact that, even if the inputs have been normalized to have zero mean and unit standard deviation, weighting the coefficient of different physical signals, like pressure, pressure gradients and winds in the same way could not be optimal. A possible solution would be to group the inputs into G disjoint classes $\mathcal{U}_g$ of physically similar signals and then use different scaling factors, $\lambda_1, ..., \lambda_G$, in the cost function

$$V_{\lambda_1,...,\lambda_G,s}(\theta) = V_s(\theta) + \sum_{g=1}^{G} \left(\lambda_g \sum_{j\in\mathcal{U}_g} ||B_j|| \right), \quad (8)$$

in the same style as [Bach et al. 2004, Bach 2008, Huang and Zhang 2010]. This will however introduce a large number of scaling factors λ_g, that have to be estimated by cross-validation, hence it is postponed to future work.

7. CONCLUSIONS

In this paper we show that using only high tide events and real wind data instead of ECMWF predictions, very good predictions of some exceptional tide events can be obtained. We have used Group-LASSO techniques to check what inputs in [Parise and Picci 2013] are really relevant for prediction. This technique should be used with caution as it should be applied only for selecting inputs of the same physical nature.

Table 3. Inputs set to zero by Group-LASSO for different sets of free parameters and λ

all

	pressure				squared p. gradients					winds U				winds V			
λ	Ve	Ge	Al	Ba	TR	PR	ZP	ST	DB	V	B	G	D	V	B	G	D
0.2			0	0													
0.3			0	0				0									
0.4			0	0				0			0						
0.5	0		0	0				0			0						

pg

	squared p. gradients				
λ	TR	PR	ZP	ST	DB
0.8–1.5		0			

winds

	winds U				winds V			
λ	V	B	G	D	V	B	G	D
0.7 –1						0		
1.1–1.4		0				0		
1.5		0			0	0		

Table 4. Nomenclature used for the models

NAME	DATA SET	PARAMETERS		ID. MET.			NUM. INPUT
		free	others fix to	cost	s	λ	
arxA	$\mathcal{A}$	all	-	PEM	-	-	9
arxB	$\mathcal{B}$	all	-	PEM	-	-	17
arxC	$\mathcal{C}$	all	-	PEM	-	-	17
arxA45	$\mathcal{A}$	all inputs	arxA	(6)	45	-	9
arxB45	$\mathcal{B}$	all inputs	arxB	(6)	45	-	17
arxC45	$\mathcal{C}$	all inputs	arxC	(6)	45	-	17
arxD45	$\mathcal{D}$	all inputs	arxC	(6)	45	-	12
arxE45	$\mathcal{E}$	all inputs	arxC	(6)	45	-	13
arxF45	$\mathcal{F}$	all inputs	arxC	(6)	45	-	15
arxC45La	$\mathcal{C}$	all inputs	arxC45	(7)	45	0.5	12
arxC45Lg	$\mathcal{C}$	pressure gr.	arxC45	(7)	45	1	16
arxC45Lw	$\mathcal{C}$	winds	arxC45	(7)	45	0.7	16

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