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Wind gust estimation by combining a numerical weather prediction model and statistical post-processing

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Abstract

The continuous rise of off-shore activities such as the development of wind farms requires a reliable operational support in order to minimize cost drawbacks and secure operations during the different stages of associated projects. One of the most important parameters for this kind of analysis is wind gustiness. The objective of the study is the development of a methodology for the surface wind gust estimation based on Numerical Weather Prediction Models and statistical post processing. The obtained method has been tested over the offshore west coastline of the United States and evaluated utilizing observational data from the NOAA's buoy network.

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Keywords: wind, wind gust, Kalman filters, forecasting, numerical weather prediction models, operational meteorology

1. Introduction

The continuous rise of offshore and nearshore activities and the development of structures such as wind farms require the employment of state-of-the-art risk assessment techniques [1,2]. These techniques depend on environmental characteristics that affect the activities in question, such as wind speed and wave height. Risk analysis has a rather climatological character and sets the safety standards that should be followed on the structural design.

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Beyond the risk analysis that is performed a priori, a reliable operational support is also needed in order to minimize cost drawbacks and human danger during the construction and the functioning stage as well as during maintenance activities. One critical parameter for this type of analysis, is the presence and magnitude of surface wind gusts, which is defined as the maximum observed wind speed over a period of time [3,4]. More than one gust definitions are proposed in the literature for wind gusts. For example, Extreme Operating Gust (EOG) and Extreme Coherent Gust (ECG) are described within the IEC 61400 standard for wind energy [5]. Moreover, several parameterizations and formulas are applied for their description and estimation.

The purpose of this work is the development of a wind gust forecasting methodology combining a Numerical Weather Prediction (NWP) model and a dynamical statistical tool based on Kalman filtering. To this end, the methodology adopted in this work is based on a physical parameterization that takes into account all the processes in gust formation, namely Wind Gust Estimate (WGE) methodology [6]. This has been applied in a number of studies [7-12] with interesting and promising results and was implemented to function within the framework of the atmospheric modeling system SKIRON/Dust [13]. The model was run operationally for four selected months with a relatively coarse resolution (small resource demands). The results were evaluated using observational data from NOAA's buoy network in the West Coast of the United States. Furthermore, for selected cases a Kalman filter methodology [14,15] was used for the removal of systematic errors, giving a more accurate estimation of forecasted wind gusts.

2. Experimental design

2.1. SKIRON/Dust Modeling System

SKIRON/Dust is a modeling system developed at the University of Athens from the Atmospheric Modeling and Weather Forecasting Group [13,16] in the framework of National and European Union (EU) funded projects like SKIRON, MEDUSE (Mediterranean Dust Experiment), ADIOS (Atmospheric Deposition and Impact on the Open Mediterranean Sea), CIRCE (Climate Change and Impact Research) and most recently MARINA (Marine Renewable Integrated Application Platform). Recently the model was updated to include the Rapid Radiative Transfer Model– RRTMG [17-20]. Further details on the various model parameterization schemes and capabilities can be found in the above mentioned studies and the references therein.

2.2. Parameterization of Surface Wind Gusts in SKIRON/Dust

The processes leading to gust formation vary among boundary-layer turbulence, deep convection, mountain waves and wake phenomena [21]. These phenomena are difficult to be properly resolved by NWP systems [21,22] without the need of considerable computational resources. In addition, the subscale interactions are not always sufficiently described and generate errors or uncertainties.

In general, gust forecasting is based on semi-empirical formulas derived from experimental studies [23-25], statistical models (using observations, ex. MOS - Model Output Statistics [26,27]) and physical parameterizations that take into account atmospheric conditions in the processes of gust formation.

In this study an integrated methodology for the prediction of wind gusts is proposed based on a NWP model and a dynamical optimization statistical algorithm. The main gust forecasting scheme adopted is the WGE method as suggested by Brasseur [6]. According to this approach, the turbulent wind fields of the boundary layer can be considered as an overlay of a large number of eddies with different sizes. Larger eddies have the scale of the depth of the boundary layer, while the smaller ones rapidly dissipate through friction. This leads to momentum transportation both upwards and downwards. Under specific conditions, air parcels within eddies may deflect toward the surface, leading to gusty type wind fluctuations [7]. These processes have been incorporated in the SKIRON/Dust modeling framework, allowing the estimation of wind gusts at the surface.

2.3. Kalman Filters

Numerical weather prediction models often exhibit systematic errors in the forecast of certain meteorological parameters. This can be attributed to the difficulties of the models to handle sub-grid processes and to possible drawbacks of the used parameterizations. In this study the parameterization for the calculation of wind gusts is mostly affected by surface fluxes and the outcome may be exposed to systematic errors. The persistence of the mentioned errors could be traced back to the local characteristics of the sites under study.

For dealing with the above mentioned problems, a polynomial Kalman filtering local adaptation model is proposed. The main goal is the estimation of the bias y_t as a function of the model output m_t (at the same time step):

$$y_t = x_{1,t} + x_{2,t} * m_t + x_{3,t} * m_t^2 + x_{4,t} * m_t^3 + V_t \qquad (1)$$

where the coefficients ($x_{i,t}$) are the parameters that have to be estimated by the filter and V_t the Gaussian nonsystematic error.

Based on this, observations are combined with recent forecasts with weights that minimize the corresponding biases. More details can be found in [14,15,28-32].

In our case the adopted statistical model was found to be functioning satisfactory in linear mode and was applied directly to the wind gust as it is calculated from the model forecasts with a training period set to 24 h. The system was developed for the correction of three different subsets that correspond to the first, the second and the third day of the forecast (0-24h/ 24-48h/ 48-72h) respectively. The main advantage of the proposed methodology is the easy adaptation to the observations and the short training period needed for the application.

2.4. Model Setup – Data used

In order to evaluate the model estimated wind gust, a series of test runs were carried out. The model was integrated for a period of four months (July and October of 2014 and January and March of 2015) over an area covering a large part of the West Coast of the American continent and the neighboring part of the Pacific Ocean. The testing period was selected with two criteria: 1) including a month from each season, so to check potential deviations and 2) ensuring availability of data from the buoys. The computational domain is shown in Fig. 1. The horizontal grid increment was 0.07 degrees (approximately ~7km) while on the vertical 45 levels were used, stretching from the surface up to 20 km. Daily NCEP GFS operational fields (horizontal resolution of 0.5 degrees) were used for initial and lateral boundary conditions. The main reason reanalysis fields were not used in this study is that we needed to evaluate the capabilities of a gust forecasting system in operational mode.

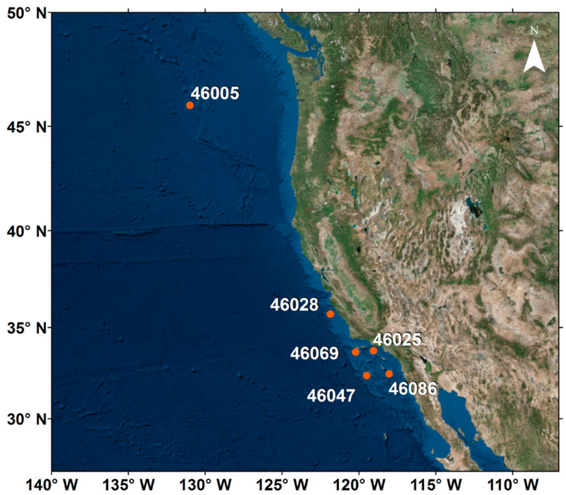

Fig. 1. SKIRON domain and the location of the six selected stations of the NOAA's National Data Buoy Center with code numbers 46005, 46025, 46028, 46047, 46086 and 46069.

The time step of the model was set at 20 sec and the radiation driver was invoked every 15 min. The model was modified to provide outputs every 10 minutes to correspond with the actual data available (as explained below) running in operational mode: For each day under study the model provided 72-hours forecasts. This allowed us to further examine the capabilities of the method applied for different forecasting horizons (24h, 48h and 72h forecasts).

For evaluating the wind gust parameterization scheme, observations from NOAA's National Data Buoy Center were used. The location of the buoys is illustrated in Fig. 1. These stations provide wind gust data as the maximum 5-second peak gust during the measurement hour, reported at the last hourly 10-minute segment. The specific buoys were selected according to data availability for the months under consideration.

2.5. Statistical Methods of Evaluation

A wide variety of forecast verification procedures exists and they all involve the study of the relationship between a forecast or set of forecasts and the corresponding observations of the predictant that in our case is the "surface wind gusts". In the present work, the evaluation of the proposed methodology was based on five distinct statistical values: the Coefficient of Determination, the Root Mean Square Error, the Bias, the Mean Normalized Bias and the Nash-Sutcliffe model efficiency coefficient [33,34].

The first four are rather common indices. Concerning the Nash-Sutcliffe model efficiency coefficient, it varies from $-\infty$ to 1, where 1 indicates the perfect match between observations and model predictions. A zero value suggests that the accuracy of the model is as good as the accuracy of the mean value of observations.

3. Results and Discussion

Using the model output and the wind gust data for the testing period (July and October of 2014, January and March of 2015) wind gust time series were evaluated against corresponding observations. An indicative example is presented in Fig. 2 for January 2015 for station 46028, (24h, 48h and 72h forecasts).

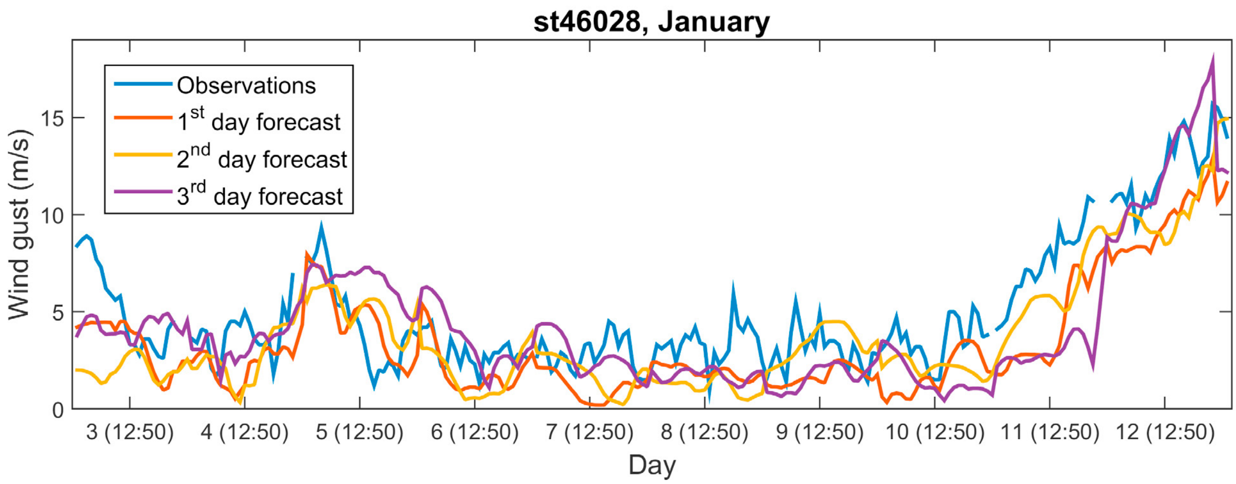

Fig. 2. Time-series of buoy data (blue line) and model forecasts for 24h (red line), 48h (yellow line) and 72h (purple line) forecasts.

It is apparent that the 1st day forecasts exhibits the best agreement between model results and data. The 2nd and 3rd day forecasts deviate from the measured gusts, especially the minimum and maximum values. This is something that was expected since the errors in NWP forecasts usually grow with the length of the forecasting horizon. This example is a first indication that the methodology applied in the SKIRON/Dust model for wind gust calculations is solid and provides acceptable results. However, in order to reach more clear and consistent evaluation results of the applied parameterization, the distributions of the number of wind gust occurrences are presented in Fig. 3a-f.

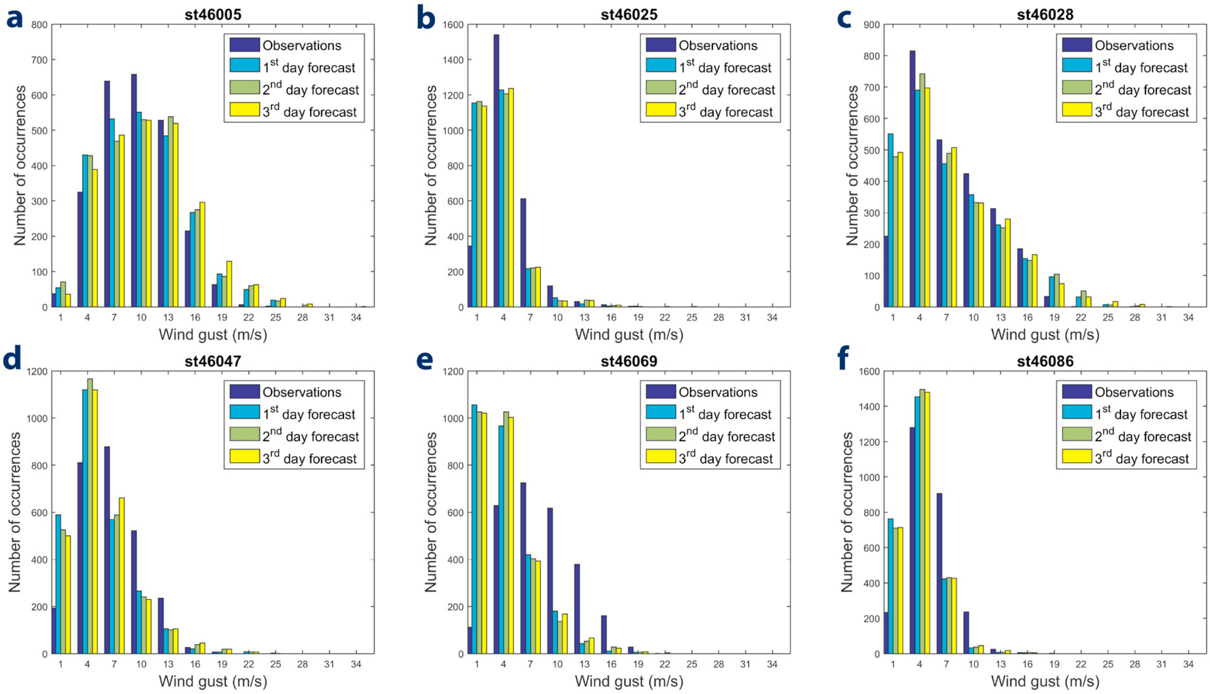

Fig. 3. Histograms for the number of occurrences of each wind gust bin for the observations (purple) and the corresponding model results for 24h (blue), 48h (green) and 72h (yellow) forecasts.

Moreover, a number of statistical scores were calculated for the entire simulation period and for the three forecasting days [34]. The results are presented in Table 1. This analysis proves that the model manages to capture the wind gust distributions in most of the cases. SKIRON performs well for the first forecasting day, with all statistical scores deviating as the forecasting horizon increases. For the second and third day forecasts it is increasingly difficult to accurately describe wind gusts due to truncation and parameterization errors. Generally in operational forecasting the model accuracy is limited both by the rapid divergence of nearby initial conditions and by deficiencies in the core model [22], thus deviating more from the actual conditions, as the forecasting horizon increases. An exception of this pattern is recorded in the statistics of St46086. However, the magnitude of the increase in the accuracy is not statistically significant and can be attributed to the limited length of the timeseries.

The best statistical scores for the first day forecasts are reached in Station 46028 with Bias and RMSE of -0.471 and 2.554 respectively. The Normalized Bias is also close to 0 (-0.066) and the Nash-Sutcliffe coefficient closer to the ideal value of 1 (0.656). This indicates that the model was able to properly capture the atmospheric parameters needed for the wind gust parameterization leading to acceptable results. At the same time, the model forecasts that correspond to the offshore Station 46005, exhibit a satisfactory performance according to the statistical indices of Bias (0.224) and RMSE (2.45). The Normalized Bias and Nash-Sutcliffe coefficient have values of 0.026 and 0.594 respectively for the 1st day of forecasting period. It is interesting to note that for buoy stations located close to the shore the model underestimated the measured wind gusts. This can be attributed to the representation of the coastline and topographical variation of the area, the grid structure of the NWP model and the air-sea-land interaction processes. On the contrary, over open sea areas the system overestimates the buoy observation. This may be due to the drag coefficient estimation through the parameterizations implemented in the modeling system and to problems associated with buoy measurements especially in high wave conditions.

Table 1: Statistical scores between measured wind gusts and the corresponding model results for 1,2 and 3 days forecasts.

Station	Forecast Day	R^2	RMSE	Bias	Normalized Bias	Nash-Sutcliffe
	1st	0.743	2.450	0.224	0.0263	0.594
St46005	2nd	0.544	3.337	0.438	0.078	0.248
	3rd	0.573	3.365	0.853	0.124	0.235
	1st	0.486	2.322	-1.541	-0.291	-0.031
St46025	2nd	0.409	2.495	-1.470	-0.273	-0.191
	3rd	0.362	2.544	-1.511	-0.274	-0.238
	1st	0.768	2.554	-0.471	-0.066	0.656
St46028	2nd	0.699	2.954	-0.316	-0.015	0.541
	3rd	0.646	3.176	-0.307	-0.001	0.469
	1st	0.451	3.258	-1.848	-0.225	-0.001
St46047	2nd	0.409	3.314	-1.683	-0.182	-0.035
	3rd	0.338	3.476	-1.583	-0.138	-0.138
	1st	0.615	2.369	-1.901	0.318	-0.146
St46086	2nd	0.623	2.246	-1.741	0.272	-0.056
	3rd	0.623	2.219	-1.642	0.263	-0.012
	1st	0.369	5.340	-4.265	0.540	-0.800
St46069	2nd	0.321	5.375	-4.205	0.562	-0.883
	3rd	0.269	5.436	-4.166	0.569	-0.944

Contrary to the overall good performance of the proposed modeling system, Station 46069 exhibits low statistical scores with a high RMSE value reaching 5.34 and a bias of -4.265 for the first day forecast. Accordingly, the normalized bias is 0.54 and the Coefficient of Determination is the lowest at 0.369. Due to these deviations from the actual wind gust data, a Kalman filter methodology was applied in the model output as described in section 2.3. Based on the corrected model data, the wind gust distributions are presented in Fig. 4a-c for the 1st, 2nd, and 3rd day.

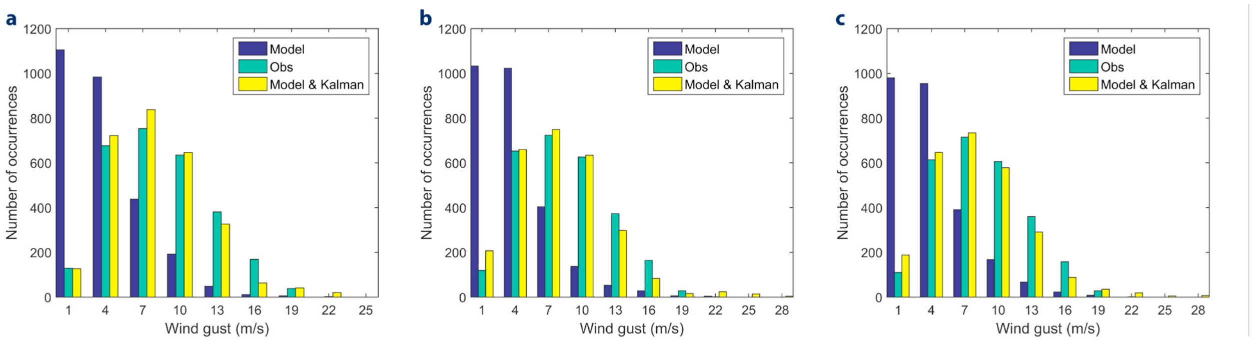

Fig. 4. Histograms for the number of occurrences of each wind gust bin for the uncorrected model data (blue), the observations (teal) and the corrected model results (yellow) for 24h (a), 48h (b) and 72h (c) forecasts.

It is obvious that the use of the Kalman filter methodology improved significantly the forecasted results. The statistical scores were recalculated for the three forecasting days (Table 2). The Bias has improved by 90% for the 1st day, by 89% for the 2nd day and by 88% for the 3rd day. This is something expected, since the Kalman filter methodology is mainly a bias correction technique. Moreover most of the other statistical figures have also been improved considerably. The Nash-Sutcliffe coefficient was improved by 109% for the 1st day, by 86% for the 2nd day and by 77% for the 3rd day. The RMSE decreased by 25% for the 1st day, by 29% for the 2nd day and by 27% for the 3rd day. Finally the Normalized Bias improved by 12% for the 1st day and by 9% for the 2nd and the 3rd day. The only index with no real improvement was the coefficient of determination. That is something rather expected, since the application of the filters tends to create phase shifts in the timeseries that may lead to weaker linear correlation. It is also noticeable that by using Kalman filters we were able to improve wind gust forecasts for all three days that is considered as important for operational systems.

The same methodology was applied to the station 46086, in order to examine the validity of the method in cases where the model does not deviate much from the measurements. The corresponding statistical scores are presented in the same Table (2). There is a noticeable improvement concerning the Bias. Accordingly RMSE decreased by 27%, 26% and 25% for 1st, 2nd and 3rd day forecasts respectively, results that underline a decent improvement. At the same time, the Nash-Sutcliffe coefficient improved significantly for all forecasting periods. Finally, the Normalized Bias improved as expected while the coefficient of determination decreased (~21-34%) for the reasons discussed in the previous case.

The above analysis indicates that the applied methodology can be a valuable tool for forecasting surface wind gusts for at least a three days forecasting horizon.

Table 2: Updated statistical scores between measured wind gusts and the corrected model results for 1, 2 and 3 days forecasts for buoys 46069 and 46086.

	Forecast day	R^2	RMSE	Bias	Normalized Bias	Nash-Sutcliffe
Station 46069	1st	0.277	3.82	-0.419	0.474	0.079
	2nd	0.227	4.148	-0.438	0.509	-0.122
	3rd	0.194	4.302	-0.467	0.519	-0.217
Station 46086	1st	0.467	1.720	0.244	0.126	0.391
	2nd	0.476	1.665	0.137	0.079	0.419
	3rd	0.492	1.671	0.101	0.071	0.426

4. Concluding remarks

In this study an advanced technique for estimating surface wind gusts is proposed by combining dynamic and statistical techniques. Based on the work of Brasseur [6], the SKIRON/Dust limited area model has been modified to provide wind gust forecasts, addressing the increased needs for reliable extreme weather forecasting. The model was run for a period of four months in forecasting mode and several statistical scores were calculated for three forecasting days, namely 24h (1st day forecasts), 48h (2nd day forecasts) and 72h (3rd day forecasts), using data from the NOAA's National Data Buoy Center. In addition a dynamical statistical methodology is proposed to correct the model results by using Kalman filters.

In most of the evaluation cases the system had a successful performance according to various calculated statistical indices. This was the case for all three forecasting periods, with 1st day forecasts giving the best results in the majority of the test runs. For locations close to the coastline the model underestimated the measured wind gusts mainly due to the poor representation of land-water boundaries and therefore the associated processes.

A Kalman filter optimization system has been applied in order to correct the model forecasts with very promising results. The procedure improved the statistical scores significantly proving that it can be used in operational wind forecasting systems.

Concluding, we can note that a combination of a NWP wind gust estimating system and a Kalman post process filter can be used in forecasting facilities that support offshore wind farms and other installations especially for the simulation extreme weather events.

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References

[1] Patlakas, P., Galanis, G., Barranger, N., Kallos, G. (2016) "Extreme wind events in a complex maritime environment: ways of quantification." J. Wind Eng. Ind. Aerodyn. DOI information: 10.1016/j.jweia.2015.11.006

[2] Larsén X.G., Badger J., Hahmann A., Ott S. (2011) "Extreme wind atlas from the selective dynamical downscaling method." In: Proceedings of European Wind Energy Conference and Exhibition. 2011.

[3] World Meteorological Organization (1987) "The Measurement of Gustiness at Routine Wind Stations: A Review (A.C.M. Beljaars)." (Instruments and Observing Methods Report No. 31), Geneva.

[4] Friedrichs, P., M. Gober, S. Bentzien, A. Lenz, and R. Krampitz (2009) "A probabilistic analysis of wind gusts using extreme value statistics." Met. Zeit., 18, 615–629.

[5] TC88 WG1. IEC 61400-1 Wind turbines : Design requirements. (2005)

[6] Brasseur, O. (2001) "Development and application of a physical approach to estimating wind gust.", Mon. Weather Rev.,129,5-25, DOI:http://dx.doi.org/10.1175/1520-0493(2001)129<0005:DAAOAP>2.0.CO;2

[7] Goyette, S., O. Brasseur, and M. Beniston, (2003) "Application of a new wind gust parameterization: Multiscale case studies performed with the canadian regional climate model." J. Geophys. Res., 108, D13, 4374., doi:10.1029/2002JD002646, 2003.

[8] Adams, N. (2004) "A numerical modeling study of the weather in east antarctica and the surrounding southern ocean." Wea. Forecast., 19, 653–672.

[9] Nilsson, C., S. Goyette, and L. Bärring (2007) "Relating forest damage data to the wind field from high- resolution rcm simulations: Case study of anatol striking Sweden in December 1999." Global and Planetary Change, 57, 161–176.

[10] Cheung, P., C. C. Lam, and P. W. Chan (2008) "Numerical simulations of wind gusts in terrain-disrupted airflow at the Hong Kong international airport." P2.34, 13th Conference on Mountain Meteorology, Whistler, BC, Canada, AMS.

[11] Pinto, J. G., C. P. Neuhaus, A. Kruger, and M. Kerschgens (2009) "Assessment of the wind gust estimate method in mesoscale modelling of storm events over west Germany." Met. Zeit., 18, 495–506.

[12] Chan, P. W., C. C. Lam, and P. Cheung (2011) "Numerical simulation of wind gusts in intense convective weather and terrain-disrupted airflow." Atmsfera, 24, 287–309.

[13] Spyrou, C., Mitsakou, C., Kallos, G., Louka, P., and Vlastou, G. (2010) "An improved limited area model for describing the dust cycle in the atmosphere." J. Geophys. Res., 115, D17211, doi:10.1029/2009JD013682, 2010.

[14] Galanis,G. ,Louka,P., Katsafados,P., Pytharoulis,I., Kallos,G. (2006) "Applications of Kalman filters based on non-linear functions to numerical weather predictions." Ann. Geophys.24, 2451–2460.

[15] Louka, P., Galanis,G., Siebert,N., Kariniotakis,G., Katsafados,P., Pytharoulis,I., Kallos, G. (2008) "Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering." J.WindEng.Ind.Aerodyn.96, 2348–2362.

[16] Kallos, G., V. Kotroni, K. Lagouvardos, and A. Papadopoulos (1998) "On the long-range transport of air pollutants from Europe to Africa." Geophysical Research Letters. 25, No 5, 619-622.

[17] Clough, S.A., Shephard, M.W., Mlawer, E.J., Delamere, J.S., Iacono, M.J., Cady-Pereira, K., Boukabara, S., Brown, P.D. (2005) "Atmospheric radiative transfer modeling: a summary of the AER codes." J. Quant. Spectrosc. Radiat. Transfer., 91, 233-244, 2005

[18] Morcrette, J.-J. (2001) "Impact of the radiation-transfer scheme RRTM in the ECMWF forecasting system." ECMWF Newsletter No. 91, 2001

[19] Iacono, M.J., Delamere, J.S., Mlawer, E.J., Clough, S.A. (2003) "Evaluation of upper tropospheric water vapor in the NCAR community climate model (CCM3) using modeled and observed HIRS radiances." J. Geophys. Res.,108(D2),4037, doi:10.1029/2002JD002539, 2003

[20] Spyrou, C., Kallos, G., Mitsakou, C., Athanasiadis, P., Kalogeri, C., Iacono, M. J. (2013) "Modeling the radiative effects of desert dust on weather and regional climate." Atmos. Chem. Phys., 13, 5489–5504, doi:10.5194/acp-13-5489-2013, 2013.

[21] Sheridan, P. (2011) "Review of techniques and research for gust forecasting and parameterization." Forecasting Research Technical Report 570, Met Office, 2011.

[22] Orrell D., L. Smith, J. Barkmeijer, and T. N. Palmer (2001) "Model error in weather forecasting, Nonlinear Processes in Geophysics." (2001) 8: 357–371.

[23] Weggel, J. R. (1999) "Maximum daily wind gusts related to mean daily wind speed." J. Struct. Eng., 125, 465– 468, 1999.

[24] Schulz, J.-P., and E. Heise (2003) "A new scheme for diagnosing near-surface convective gusts." COSMO Newsletter No. 3.

[25] Simon, A., A. Kann, M. Nestiak, I. Meirold-Mautner, A. Horvath, K. Csirmaz, O. Ulbert, and C. Gruber (2011) "Nowcasting and very short range forecasting of wind gusts generated by deep convection." General Assembly 2011, Vienna, Austria, EGU.

[26] Glahn, B., and J. P. Dallavalle (2006) "Gridded mos–techniques, status, and plans." 18th Conference on Probability and Statistics in the Atmospheric Sciences, Atlanta, AMS.

[27] Barrett, J. H., and D. A. Short (2008) "Peak wind tool for general forecasting." nasa contractor report nasa/cr-2008-214743. Technical report, NASA Applied Meteorology Unit, Kennedy Space Center, Florida.

[28] Kalman R.E. (1960) "A New Approach to Linear Filtering and Prediction Problems." Transactions of the ASME – Journal of Basic Engineering, 82 (Series D): 35-45,1960 by ASME

[29] Kalnay,E. (2002) "Atmospheric Modeling, Data Assimilation and Predictability." Cambridge, Cambridge University Press,p.341 2003.

[30] Galanis G., Emmanouil G., Kallos G., Chu P. C. (2009) "A new methodology for the extension of the impact in sea wave assimilation systems," Ocean Dynamics, 59 (3), 523-535.

[31] Galanis G., Chu P.C. and Kallos G. (2011) "Statistical post processes for the improvement of the results of numerical wave prediction models. A combination of Kolmogorov-Zurbenko and Kalman filters." Journal of Operational Oceanography, Vol 4 (1), pp. 23-31.

[32] Stathopoulos, C., A. Kaperoni, G Galanis and G. Kallos (2013) "Windpower prediction based on numerical and statistical models." J.WindEng.Ind.Aerodyn.112, 25–38.

[33] Nash, J. E. and J. V. Sutcliffe (1970) "River flow forecasting through conceptual models part I — A discussion of principles." Journal of Hydrology, 10 (3), 282–290.

[34] Wilks, Daniel S. (2006) "Statistical Methods in the Atmospheric Sciences, Second Edition." Academic Press, London. ISBN 13: 978-0-12-751966-1.