1 F	Real-time weather forecasting in the Western Mediterranean Basin: an application
2	of the RAMS model
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25ABSTRACT

26A regional forecasting system based on the Regional Atmospheric Modeling System 27(RAMS) is being run at the CEAM Foundation. The model is started twice daily with a 28 forecast range of 72 hours. For the period June 2007 to August 2010 the verification of 29the model has been done using a series of automatic meteorological stations from the 30CEAM network and located within the Valencia Region (Western Mediterranean 31Basin). Air temperature, relative humidity and wind speed and direction of the output of 32the model have been compared with observations. For these variables, an operational 33verification has been performed by computing different statistical scores for 18 weather 34stations. This verification process has been carried out for each season of the year 35separately. As a result, it has been revealed that the model presents significant 36 differences in the forecast of the meteorological variables analysed throughout the year. 37Moreover, due to the physical complexity of the area of study, the model presents 38different degree of accuracy between coastal and inland stations. Precipitation has also 39been verified by means of yes/no contingency tables as well as scatter plots. These 40tables have been built using 4 specific thresholds that have permitted to compute some 41 categorical statistics. From the results found, it is shown that the precipitation forecast 42in the area of study is in general over-predicted, but with marked differences between 43the seasons of the year. Finally, dividing the available data by season of the year, has 44permitted us to analyse differences in the observed patterns for the magnitudes 45mentioned above. These results have been used to better understand the behaviour of the 46RAMS model within the Valencia Region.

49verification, numerical weather prediction, natural hazards, warning and alert systems.
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Keywords: RAMS model, operational forecasting, mesoscale modelling, model 49verification, numerical weather prediction, natural hazards, warning and alert systems.

721. Introduction

The Regional Atmospheric Modeling System (RAMS) has been implemented 74within a real-time forecasting system over the Western Mediterranean Basin, precisely 75in the area delimited by the Valencia Region (Fig. 1). This area exhibits a relevant in-76terest from a meteorological point of view, as it is particularly sensitive to certain severe 77weather events. Among them, we must highlight episodes of forest fires (Gómez-Te-78jedor et al., 1999) and heat waves (Miró et al., 2006; Gómez et al., 2010; Gómez et al., 792013) in the summer. In addition, during the late summer and autumn, episodes of tor-80rential rains are also common over this region (Millán et al., 1995; Estrela et al., 2002; 81Millán et al., 2005). Finally, during the cold period of the year, the Valencia Region is 82affected by low temperatures, mainly related to the entrance of northerly Arctic air, en-83trance of north-easterly continental polar air or anticyclonic situations (Millán et al., 842005; Estrela et al., 2010).

The sensitivity of the Valencia Region to climate hazards encouraged us to 86design and develop a meteorological real-time forecasting system for this area (Gómez 87et al., 2010). Severe weather events in the Valencia Region has been studied at the 88CEAM (Centro de Estudios Ambientales de Mediterráneo; Mediterranean Center for 89Environmental Studies) Foundation, using the Regional Atmospheric Modeling System 90(RAMS). Besides, RAMS has also been used in the CEAM Foundation within different 91research projects (Gómez et al., 2010). As a result, the operational forecasting system 92running over the Valencia Region is based on this mesoscale meteorological model. 93Taking into account the climatic and physical characteristics of this region, it may be 94seen that the usage of an atmospheric model operating at a high resolution would be 95useful as a warning and alert forecasting tool and to simulate the significant local 96circulations and processes that take place over this region. For the current study, RAMS 97has been operationally implemented for the whole Valencia Region (Fig. 1) at a 3 x 3 98km grid horizontal resolution. Besides, the model has been running on a daily basis for 99the period June 2007 to August 2010.

100 The attention of the current work is mainly focused on the analysis and 101evaluation of the RAMS high-resolution weather forecasts produced by the operational 102forecasting system implemented for the Valencia Region. To do this, we have taken 103advantage of the automatic weather stations from the CEAM network, and located 104within this area (Corell-Custardoy et al., 2010). Near-surface meteorological 105observations are compared with the RAMS forecasts in an operational evaluation. 106Instead of performing a verification of the model for the whole year, the evaluation 107procedure has been performed by dividing the available information by season of the 108year. This separation of the data would permit to identify the occurrence and 109permanence of meteorological processes typical of a concrete season of the year. 110Besides, this information is truly useful in order to assess the model ability to predict 111the corresponding atmospheric condition. On the other hand, coastal stations have been 112isolated from inland ones, to evaluate differences between station location, as was 113already done by Gómez et al. (2013).

114 The paper is structured as follows. Firstly, section 2 presents the data and the 115verification methodology. Secondly, section 3 includes the results. And finally, section 1164 is devoted to the conclusions of this work.

1172. Data and verification methodology

1182.1. RAMS model

119 In this study, the RAMS model in its version 4.4 has been used. The following 120two-way interactive nesting domains (Fig. 1) is adopted. Firstly, Grid 1 covers the 121southern part of Europe at a 48-km horizontal grid resolution and the Mediterranean. 122Secondly, Grid 2 covers the Iberian Peninsula and the western Mediterranean with a 123grid resolution of 12 km. Finally, a high resolution domain (3 km) (Grid 3) includes the 124Valencia Region. In the vertical, a 24-level stretched scheme has been selected, with a 12550-m spacing near the surface increasing gradually up to 1000 m near the model top at 12611 000 m. A summary of the horizontal and vertical grid parameters is provided in 127Table 1. Although the number of vertical levels does not permit a so high model top, 128this grid configuration has been selected looking for a compromise between the model 129being able to simulate the most significant local circulations over this region in a time 130where the forecast is useful and the computational resources available when the model 131was implemented that way. Nevertheless, as only surface variables are analysed in the 132current work, we strongly believe that the model top employed is adequate to fulfill the 133purpose of this study. Furthermore, we must remark that, in terms of temperature and 134 wind speed and direction, the results found in the present study are comparable to those 135 found in other studies using additional vertical levels and reaching a higher model top 136(Palau et al., 2005; Pérez-Landa et al., 2007).

137 The RAMS model includes different options for parameterizing physical 138processes (Pielke, 2002; Cotton et al., 2003). In the present study, the Mellor and 139Yamada (1982) level 2.5 turbulence parameterization is used. Besides, a full-column 140two-stream single-band radiation scheme that accounts for clouds to calculate short-141wave and long-wave radiation (Chen and Cotton, 1983), and the cloud and precipitation 142microphysics scheme from Walko et al. (1995) is applied in all the domains. The Kuo143modified parameterization of sub-grid scale convection processes is used in the coarse 144domain (Molinari, 1985), whereas grids 2 and 3 utilizes explicit convection only. This 145convective scheme has been adopted based on previous studies performed within the 146area of study (Palau et al., 2005; Pérez-Landa et al., 2007). Finally, the LEAF-2 soil-147vegetation surface scheme was used to calculate sensible and latent heat fluxes 148exchanged with the atmosphere, using prognostic equations for soil moisture and 149temperature (Walko et al., 2000).

RAMS initial and boundary conditions are derived from the operational global Is1model of the National Centre for Environmental Prediction (NCEP) Global Forecasting Is2System (GFS), at 6 h intervals and 1 x 1 degree resolution globally, using a Four-Is3Dimensional Data Assimilation (FDDA) technique applied to define the forcing at the Is4lateral boundaries of the outermost five grid cells of the largest domain. Weather Is5forecasts were performed twice a day, at 0000 and 1200 UTC using the GFS forecast Is6grid from its forecast cycle 12-h earlier, and for a forecast range of three complete days Is7(today, tomorrow and the day after tomorrow). However, only the information Is8corresponding to the 0000 UTC RAMS forecast was stored as will be described later. Is9Finally, RAMS forecast outputs are available once per hour for display and analysis I60purposes. Thus, the model verification has been limited in time to a frequency of 1-h, I61regardless of the frequency of available observational data.

1622.2. Observational data

163 The CEAM automatic surface weather stations network provides a good 164coverage of observations within the Valencia Region (Corell-Custardoy et al., 2010). 165However, some of this meteorological stations are located in peaks at a high altitude for 166use in the research of passive fog collection (Estrela et al., 2008), that the model is not 167able to reproduce using the current configuration. Thus, we have selected those stations 168in which the model is able to properly reproduce not only the orographic and physical 169conditions of the station location but also its surroundings. In this sense, only those 170stations with a difference in altitude between the station and the corresponding grid 171point lower than 50 m have been selected to carry out the verification of the model. This 172threshold in altitude has been chosen as it is approximately the thickness of the first 173model level using the current configuration. Due to the low density of pure coastal 174stations, we have merged them with pre-coastal ones. However, the behaviour of the 175model for those sort of stations, although nearer the one observed for the coast, is in 176between this locations and those placed inland, depending on the station location (not 177shown). As a result, a total of 6 coastal stations (including pre-coastal ones) and 12 178inland stations has been selected (Fig. 1).

179 Although the CEAM weather stations network stores data in a 10-minute basis, 180hourly measures of air temperature, relative humidity, wind speed and direction and 181precipitation from this network have been used in the verification process, in order to 182match the RAMS output frequency.

1832.3. Verification procedure

184 RAMS output from the higher resolution domain are compared with the 185observations. We have developed a software tool to extract and store, for each daily 186simulation within the period June 2007 to August 2010, the hourly RAMS forecast 187temperature, relative humidity, wind speed and direction as well as precipitation at each 188selected CEAM station location using Grid 3 (Fig. 1). These data have been stored for 189the three days of simulation of the model. More information about the software 190developed may be found in Gómez et al. (2013).

191 Several processes are carried out in the RAMS evaluation. A series of statistical 192scores have been computed for each CEAM station independently (Papanastasiou, 1932010; Federico, 2011; Kotroni, 2011; Hernández-Ceballos et al., 2013). The statistical 194calculations carried out in both cases include the mean bias, root mean square error 195(RMSE) and the index of agreement (IoA) for the near-surface temperature, relative 196humidity and wind speed. Additionally, the RMSE for the vector wind difference 197(RMSE-VWD) is computed as well. Firstly, bias (or mean bias) is defined as the 198average of the simulated value minus the observed value and quantifies the systematic 199error of the model. Secondly, RMSE is the square root of the individual differences 200between simulated and observed values; it quantifies the accuracy of the model. In this 201sense, the RMSE-VWD corresponds to the RMSE of the horizontal vector-wind-202difference. In the third place, the IoA is a modified correlation coefficient that measures 203the degree to which a model's prediction is free of error. A value of 0 means complete 204disagreement while a value of 1 implies a perfect agreement. Finally, besides computing 205the mentioned statistical scores, the observed averaged value and modelled averaged 206value are computed as well for graphical depiction purposes.

In the case of precipitation, and as a difference with the results observed for 2080ther meteorological variables, no specific pattern has been found among coastal and 209inland stations. Thus, to introduce the results for this magnitude, all stations has been 210merged (Fig. 1). The verification of precipitation, includes the forecast of the total daily 211accumulated precipitation amount, starting at 0000 UTC, as well as the four 6-hourly 212accumulated precipitation forecasts of the day. With this data, a 2x2 contingency table 213(Martin et al., 2010) is then constructed for some precipitation thresholds. The values 214selected are those used by Bartzokas et al. (2010), 2, 8, 15 and 30 mm. With the 215contingency tables generated, categorical statistical scores are computed in order to 216describe particular aspects of precipitation forecast performance (Mazarakis et al., 2172009). The categorical statistics include the accuracy (AC), bias score (BIAS), 218probability of detection (POD), false alarm ratio (FAR), threat score (CSI) and the 219Heidke skill score (HSS). AC expresses the fraction of the correct forecasts. That is, the 220percentage of observed yes events in addition to correct negatives that were properly 221forecast. BIAS measures the ratio of the frequency of forecast events to the frequency of 222observed events and it indicates whether the forecast system has a tendency to under-223predict (BIAS<1) or over-predict (BIAS>1) events. POD expresses the fraction of the 224observed yes events that were correctly forecast. FAR expresses the fraction of observed 226and/or forecast events that were correctly predicted. As a result, CSI is only concerned 227with those forecasts where correct negatives are not considered. Finally, HSS measures 228the fraction of correct forecasts after eliminating those which would be correct due 229purely to random chance (Bartzokas et al., 2010).

230 Concerning precipitation, it is well known that the standard categorical 231verification statistics computed from point match-ups may lead to poorer verification 232results, specially regarding the double penalty problem (Rossa et al., 2008). Therefore, 233spatial verification methods may be desirable if the measurement data is accessible on a 234grid, as the analysis of the model data depends on its horizontal resolution. However, 235the available data in the current study is that corresponding to the rain gauge network 236(Fig. 1). Thus, the approach applied will be focused on the traditional metrics described 237above. Nevertheless, it is important to highlight that the purpose of this verification 238process is to evaluate the RAMS model precipitation for each season of the year 239separately. In this regard, the model configuration and the rain gauge available 240information is maintained throughout the whole verification period. As a consequence, 241we strongly believe that the procedure used in the present work is still helpful and 242appropriate to obtain a global evaluation of the RAMS-simulated precipitation and to 243remark the characteristics of rainfall forecasts for the different seasons of the year in the 244Valencia Region.

245 The operational verification for all the meteorological variables has been carried 246out for all days of simulation independently: today, tomorrow and the day after 247tomorrow, and all seasons of the year separately. Dividing the information for each day 248of simulation will permit to evaluate the degree of the forecasts as the simulation 249progresses and define the skill of the model that will be expected from its initialization. 250Dividing the available data for each season would permit to evaluate the skill of the 251model in reproducing the meteorological characteristics within the Valencia Region for 252each season. Winter is defined by the months December-February, spring for months 253March-May, summer from June to August and the fall within the period September-254November. From the period of verification, a total of 3 winters (2007-2008, 2008-2009, 2552009-2010), springs (2008, 2009 and 2010) and falls (2007, 2008 and 2009), and 4 256summers (2007, 2008, 2009 and 2010) have been used in this study. For each of those 257periods, the statistical scores for temperature, relative humidity, and wind speed and 258direction, has been computed for each station individually. It has been found that all 259coastal stations present similar results for a particular season of the year, and the same is 260also true for inland stations. However, the behaviour of the model in forecasting the 261evaluated magnitudes for coastal stations is rather different for that found for inland 262ones. Thus, taking this results into account and in order to clarify the presentation of the

263results, the different stations have been divided by areas: coastal and inland stations. All 264data for each sort of stations and for each season in each available year has been merged 265and a series of statistical scores have been computed again as well as merging all 266stations for each season. To make the paper clearer, we present here the differences 267between coastal and inland stations in a seasonal way taking into account all data 268available for all years. The behaviour of the model found for maximum and minimum 269temperature taking into account coastal and inland stations separately is in accordance 270with the results found over this area by Gómez et al. (2013).

2713. Results

2723.1. Temperature and Relative Humidity

The average hourly evolution of the near-surface temperature and relative 274humidity is included in Fig. 2c,d for the summer season. It is seen that, in the early 275morning until noon, the near-surface temperature is very well captured by RAMS. On 276the contrary, from this time on and at night, the model shows slightly higher 277temperatures compared to the observations. The differences between the temperatures 278observed and forecast are related to a greater deviation in the near-surface relative 279humidity. In this sense, higher disagreement in relative humidity between the 280observations and the model is found within this period of the day for both inland and 281coastal stations. In the first sort of stations, a significant difference in relative humidity 282has been found between day and night time. During the day time, the variance between 283the modelled relative humidity and the observed one is quite reduced, and the model is 284able to capture quite well the maximum temperature. In contrast, during night time, this 285difference in relative humidity raises significantly, with an overestimation of the 286minimum temperature. For coastal stations, it is also shown that the model is able to 287simulate the relative humidity observed around sunrise, with the temperatures very well 288captured for this period. Besides, the differences found between the modelled and 289observed relative humidity for the rest of the day are rather alike. Thus, as it was already 290stated by Gómez et al. (2013), during summer a different behaviour of the temperature 291is observed between day time hours and night time for both coastal and inland stations 292in the Valencia Region.

293 Within this season of the year (Table 2), the IoA of the temperature for all sta-294tions is around 0.9 for coastal stations and inland stations during day time, indicating 295that the evolution of this magnitude is very well reproduced by the model. In general, 296RAMS reproduces a slight overestimation of temperature, with a global bias of 1.0 °C 297 for the first day of simulation. It can be seen how the tendency of the model is the same 298 for day and night time. When only the coastal stations are considered, the model has a 299very little bias (0.4 °C) for the whole day. For inland stations, the model has a global 300positive bias of 2 °C. At night, more differences are observed. In this case, the tendency 301of the model is the same as the one observed during the day, producing a positive bias 302of 3 °C, compared to a bias of 0.4 °C for the day. Nevertheless, a high value of 0.7 for 303the IoA score at night is still observed. These trends are also observed in Fig. 3c,d. In 304 relation to the relative humidity, RAMS simulates this magnitude worse than it does for 305temperature (Fig. 4c,d). The IoA for the relative humidity is lower than that computed 306 for temperatures, with values between 0.5 and 0.7 approximately. The IoA is greater for 307both sort of stations during day time. It is greater than 0.7 for inland stations, i. e., repro-308ducing quite well the day-to-day evolution of relative humidity. On the contrary, at 309night, this value falls to about 0.6, indicating that the model has more difficulties in cap-310turing the evolution of this magnitude for this period of the day. The model is too dry

311both at night and during the day time, as it is reflected by a negative bias in all situations 312analysed (Figs. 2 and 4), but with different degree of accuracy for coastal and inland 313stations. In this sense, better results in the relative humidity forecasts are found for the 314night time and for coastal stations, with bias of -13 % opposite to a value of -20 % for 315inland ones and for the first day of simulation. At day time, a bias between -8 and -9 % 316is found for both sort of stations. Thus, the dry bias is more pronounced at night inland. 317In addition, there are low differences for the bias score between night and day in the 318coast. During summer time, the IoA for the relative humidity suffers a slight decrease 319for the second and third days of simulation in all cases, while both the bias and RMSE 320increase in general as the simulation progresses (not shown). Finally, the RMSE statist-321ics for temperature is about 3 °C, with higher values for inland stations at night, while 322the model shows values of RMSE around 23 % for relative humidity.

323 Similar results as those commented within the summer season are found in the 324spring, as can be seen in Table 2. However, Fig. 2a,b reflects that the difference in relat-325ive humidity both for coastal and inland locations is reduced compared to the summer.

In the winter, for inland stations, the model captures quite well the temperature 327evolution (Fig. 2g,h). However, the model has some difficulties in the daily heating and 328cooling. In contrast, the modelled and observed differences in relative humidity are 329quite reduced in the winter (Fig. 4g,h). As a consequence, the magnitude of the 330minimum temperature is better captured for this season of the year, although a delay in 331the time occurrence of about an hour is also observed. For coastal stations, the model 332has a tendency to delay the daily cooling. In this sense, it can be seen that, although the 333cooling observed stabilizes soon in the evening, the model continues this process. Thus, 334the minimum temperature is under-predicted by the model. This delay in the daily 335cooling produces the model to be also delayed in the daily heating. As a consequence, 336the forecast maximum temperatures are lower than those observed. The difference in the 337daily temperature evolution shows its relation to the relative humidity, where it can be 338seen that the significant cooling modelled by RAMS is associated with the rising curve 339of relative humidity while the observed magnitude is nearly constant during the end of 340the evening and the whole night.

Table 2 shows that the IoA for the temperature is above 0.9 during the day-time 342while it falls at night-time. Besides, low negative bias are found for coastal stations for 343the whole day. For inland stations, the model has a bias of -0.9 °C at day-time, thus pro-344ducing a slight under-prediction of the temperature observed. In contrast, the model 345shows a low over-prediction of the temperature at night, as shown in the bias score (0.8 346°C). For this sort of stations, values up to 4 °C are found for the RMSE statistics.

The IoA during the fall season (Table 2) for temperature shows values greater 348than 0.9. Thus, the model is able to capture very well the daily and day-to-day evolution 349of this magnitude. Besides, low values for the temperature bias score, below 1.0 °C, are 350also found in general for both sort of stations. In terms of relative humidity, the model 351shows a general tendency to under-predict the observations (Fig. 4e,f), but with lower 352differences than those found in the summer and the spring, and rather similar to those 353obtained for the winter season.

As shown in Fig. 4 there are significant differences in terms of relative humidity 355between the summer and the winter seasons when comparing the simulation with the 356measurements. In this sense, the summer season is characterized by a notable underes-357timation of this magnitude while the winter shows a tendency to overestimate the obser-358vations in general. As it will also be seen later for the wind field, the spring and the fall 359stay in between the other two seasons, with the spring closer to the summer results and 360the fall nearer the winter pattern.

3613.2. Wind Speed and Direction

The wind regime within the summer season (Fig. 5c,d) is characterized by the 363development of a diurnal sea-breeze advecting air from the sea to land, and a surface 364drainage wind from land to sea at night. It is seen how thermal circulations develop 365during the day, producing this advection pattern. The sea-breeze flow stabilizes during 366the central period of the day, as can be seen in the nearly flat curve described both by 367the observation and the model output for wind direction. In this case, the model 368reproduces very well the observed South-Eastern flow merging all stations. Besides, the 369summer wind transition is more marked for coastal stations both in the observations and 370the model.

The IoA for the wind speed is 0.4 for the first day of simulation merging all sort 372of stations and during day time (Table 3), while it rises up to 0.5 at night time. In the 373first case, a value of 3 m/s for bias is observed, while at night, bias is lower, with values 374about 1.1 m/s, as it was already seen above in the time series plots. These values are fair 375good, due the complexity of the flow, which is more marked during the day time. For 376wind speed, the model is too windy both at the coast and inland, with the model per-377formances better during the night in both cases (Fig. 6c,d). The RMSE is about 2 m/s 378taking into account all stations. Finally, the RMSE-VWD reflects the day-night differ-379ences for the wind speed, as was already shown in Fig. 5c,d.

380 During the spring season, RAMS is able to capture rather well the wind flow re-381gime Fig. 5a,b. For coastal stations, the transition between both breeze processes is well 382reproduced by the model. However, wind speed for this kind of stations is overestim383ated by the model. For inland stations, the model is able to capture very well both the 384wind flow regime and the daily transitions as well as the wind speed observed. Further-385more, RAMS is able to reproduce better the wind field observed at night than it does at 386day time (Fig. 6a,b), as indicated by the values of the RMSE-VWD statistics.

During the fall season, there is a marked increase in drainage flow compared to 388the sea breeze circulation, coinciding with a reduction of sunlight hours (Fig. 5e,f), 389which is more pronounced for the winter (Fig. 6g,h). In this last case, for coastal 390stations, this diurnal wind flow regime transition is maintained, although followed by a 391reduction in the regime flow amplitude. In this case, this transition is very well captured 392by the model. For inland stations, this wind flow regime is significantly reduced. In this 393case, land breeze controls the wind circulation and it is maintained practically 394throughout the whole day (Fig. 6h). RAMS captures quite well the time evolution of 395this wind flow, although it provides northerly winds. Besides, the wind speed is very 396well captured by the model for inland stations.

In terms of the model error for the wind speed (Table 3), the model is able to 398capture very well this magnitude for inland stations during the winter, with low bias 399merging all data. However, for coastal stations, the model is slightly windy. When 400taking into account all data, a bias of about 0.9 m/s is obtained. Comparing the statistics 401for the wind speed between the winter and the summer seasons, better results are found 402for this statistics within the first one, specially during the day-time. Furthermore, Fig. 6 403shows the significant differences that are reproduced by RAMS between the winter and 404the summer seasons for all sort of stations. In this sense, RAMS establishes a well 405separated transition between two wind flows of different characteristics in the summer: 406drainage wind from land to sea at night and sea-breeze during the day. In this case, as it 407was pointed before, the model remains too windy in the case of a sea-breeze flow 408compared to the observations. However, this difference is not so clear in the winter 409season, where the model reproduces a larger dispersion of the data (Fig. 6g,h), 410indicating more variability in the wind field. In the end, the spring and the fall seasons 411represents situations in between both cases described: the first one, close to the results 412found for the summer but not as notable as in this case, while the fall reproduces a 413similar pattern to the one found for the winter. In this case, it is still observed the 414transition between the summer and the winter (Fig. 6e,f).

Finally, considering the RMSE-VWD for all stations, no significant differences found comparing the different seasons of the year. However, the fall is the period like the period with the lower values of this statistics are recorded, but close to the values observed 18 within the other periods.

4193.3. Precipitation

The comparison between the modelled and the observed daily accumulated pre-421cipitation for the second day of simulation is presented in Fig. 7 for all seasons of the 422year. This figure shows that RAMS presents a clear tendency to underestimate higher 423values of observed precipitation. This is the pattern reproduced by the model throughout 424the year, independently of the corresponding season. However, the model shows the op-425posite trend for low precipitation. Moreover, RAMS forecasts large values of precipita-426tion not observed. Once again, this is the pattern followed by the model throughout the 427year, with the exception of the winter. Even though this trend is maintained for this sea-428son of the year, it is not as pronounced as the one reproduced within the other seasons.

429 When dividing the accumulated precipitation data by 6-h periods, it is observed 430that RAMS produces a significant overestimation of the accumulated rainfall for the 431 first 6-h interval (00:00-06:00 UTC) within the first day of simulation (not shown). This 432 result is not observed for other time periods. Thus, although the model shows rather 433 similar results for the three days of simulation in the second (06:00-12:00 UTC), third 434(12:00-18:00 UTC) and fourth (18:00-24:00 UTC) intervals, more differences are ob-435 served for the first 6-h period, causing unrealistic results of the forecast precipitation for 436 this whole first day of simulation. As a result, comparing the three days of simulation, it 437 is observed that the accuracy of the model slightly decreases as the simulation moves 438 forward. Nevertheless, it has been found that for the first day of simulation, the model 439 skill is lower than that found the second day, due to the mentioned overestimation dur-440 ing the period 0-6h within the first day. This result is not related to a particular season. 441 On the contrary, it is a constant for all seasons of the year. Besides, this result is not 442 found for the second and third days of simulation.

During summer, the tendency of the model to over-predict the observations is 444more notable within the period 12-18h (Fig. 8g), where more differences are found with 445the other time intervals. This result apply to the other seasons of the year, as shown in 446Fig. 8c for the spring.

From all seasons of the year, the fall is the one where the largest values of accu-448mulated rainfall are observed in the Valencia Region (Fig. 7). In this case, considerable 449precipitation is distributed along the whole day (Fig. 9). In the winter, rainfall is ob-450served throughout the whole day, with higher amount of precipitation starting in the 451second 6-h interval (06:00-12:00 UTC) (Fig. 9f). Spring and summer seasons show 452rather alike results in terms of accumulated precipitation for the different 6-h intervals. 453In this case, higher amounts are observed in the third 6-h interval (12:00-18:00 UTC), 454specially in the summer where thunderstorms are common over the area of study. These 455results of precipitation observed agree with the study of Millán et al. (2005), where it 456was pointed out that within the Valencia Region, summer thunderstorms are associated 457with the final stages of development of the combined sea breeze/upslope winds, and 458they tend to develop on the east-facing slopes of the coastal mountain ranges from noon, 459as has also been shown here.

460 Categorical statistics of the contingency tables for 2, 8, 15 and 30 mm daily pre-461 cipitation thresholds has been computed for the three days of simulation and all seasons 462of the year (Table 4). In general, it has been found that POD, CSI and HSS decreases as 463the precipitation threshold increases, with the FAR score following the opposite trend. 464In addition, for higher thresholds the model shows more difficulties in forecasting the 465observed precipitation pattern. Besides, it is important to note that the rainfall prediction 466 within the summer is poorer than in the other seasons of the year, increasing the FAR 467score. The model has a tendency to over-predict the observations in all seasons, as in-468dicated by the positive values of the bias score, being more marked for higher 469thresholds. Comparing the three days of simulation separately, the first day presents the 470largest values of POD, CSI and HSS scores, with the lowest value of FAR statistic (not 471shown). However, the accuracy of the model over this period is lower than the one com-472puted for the other two days of simulation. Besides, the bias score is higher within the 473 first day of simulation, with higher differences for larger thresholds. Once again, these 474differences seem to be related to the total precipitation forecast by the model within the 475 first 6 hours of the simulation, that was not observed. Comparing the different scores by 476season, it is seen that although the tendency of the model in the fall is the same as in the 477other seasons of the year, RAMS is more accurate in this case, specially for the highest 478thresholds. In addition, the model is skilful in reproducing the forecast of precipitation

479properly at a percentage better than 90 % in general, as indicated by the AC score. Tak-480ing into account a particular threshold, there are no significant differences between the 481four seasons of the year. The largest deviation between seasons is located in the bias 482score, specifically for the maximum thresholds selected. In this case, the rainfall ob-483served is better represented by RAMS in the fall and the winter. In contrast, the spring 484and the summer show the largest differences between the observations and the model.

The above verification process has also been followed using the four 6-h periods 486of the day. In tables 5-8 the results for the daily 6-h period of the second day of 487simulation are presented. As in Bartzokas et al. (2010), the 30 mm threshold has been 488omitted because of the too low number of events. In addition, as may be observed in the 489mentioned tables, the 15 mm threshold cannot be considered decidedly convincing for 490the same reason. For the period 00:00-06:00 UTC, there is a clear trend of the POD, CSI 491and HSS scores to decrease as the threshold increases in the spring, summer and fall. On 492the contrary, FAR increases for higher thresholds. During winter, however, this trend is 493not so clear. Moreover, within this season, the bias increases for higher thresholds, as a 494difference with the other seasons of the year.

A relevant result that has been mentioned in this section is that the model 496presents difficulties in forecasting the observed precipitation for the first day of 497simulation (not shown). Thus, larger values of bias are found within the period 00:00-49806:00 UTC compared to those found for the second and third days of simulation. As a 499result, the greatest errors found for the first day of simulation within the 24 hours are 500related to this significant overestimation of precipitation within the 00:00-06:00 UTC 501period of this day. These differences are found for all seasons of the year, being more 502notable during the summer and the spring. Besides, tables 7 and 8 show that for these 503seasons of the year, higher values of bias are produced by RAMS within the period 50412:00-18:00 UTC for the highest thresholds, as well as within 18:00-24:00 UTC. As 505introduced above, in the summer season, episodes of thunderstorms are frequent over 506the Valencia Region (Millán et al., 2005). Thus, the model is in general overestimating 507the amount of precipitation recorded in these sort of events. As a result, the 508overestimation observed in the summer and the spring for the 24-h accumulated 509precipitation is related to the high differences in the period 12:00-18:00 UTC for all 510days of simulation. In addition, for the first day of simulation, these differences are 511reinforced with those found within the period 00:00-06:00 UTC. This could be related 512to the initialization of the model. In addition, a recent study carried out by Gómez et al. 513(2011) shows the influence and the impact of convective parameterization in the RAMS 514model results for a heavy rain event within the Valencia Region. As a result, it seems 515that the effect of the convective parameterization configuration used in this operational 516forecasting system should be considered in the future in order to improve the 517precipitation forecasts over the region of study.

5184. Conclusions

The RAMS model has been running operationally for the period June 2007 to 520August 2010 within the Valencia Region. The results are used in order to develop a 521meteorological high-resolution real-time forecasting system focused on the forecast of 522meteorological and climatological hazards. The main aim of this paper has been to 523perform an evaluation of the operational forecasting system implemented in the 524Valencia Region. In this sense, a seasonal verification has been applied dividing the 525surface weather stations by coastal and inland locations. Separating both sort of stations 526permit to evaluate differences for the model forecasts in a regional way, as well as to 527obtain more information of the model skill. As a result, it has been found that 528differences arise in all variables analysed between coastal and inland stations, except for 529precipitation. Moreover, the model behaves in a different way throughout the year for 530these stations, with marked seasonal characteristics, particularly between the summer 531and the winter.

The following conclusions can be drawn according to this verification analyses. 533Firstly, temperature is rather well captured by the model for coastal stations in the 534spring and the summer. However, more differences are found during the fall and the 535winter. The time of minimum temperature in the summer is very well reproduced by the 536model, but delay is found for the rest of the seasons, specially in the fall and the winter. 537For inland stations, day time temperature is slightly overestimated in the spring and the 538summer, but is properly captured in the fall and the winter. In contrast, a significant 539over-prediction of the night time temperature is found in the spring and the summer. 540This magnitude is rather well reproduced by the model in the fall and the winter 541seasons. In addition, the model follows correctly the diurnal heating observed in the 542spring and the summer, for all kind of stations. Moreover, the model captures quite well 543the night cooling in the fall and winter. On the contrary, the model has more problems 544while simulating this process in the summer.

Secondly, the relative humidity is in general under-predicted by the model for all 546seasons of the year, but this difference is remarkably more notable during summer, both 547for coastal and inland stations. Thus, the model is too dry, specially at night and in the 548summer, producing the model to be too warm within this period of the day. In contrast, 549in the fall and winter, the tendency of the model changes from day time to night time, 550mainly in winter and for coastal stations. For inland stations within this period of the 551year, the evolution and magnitude of the relative humidity is very close to one observed. 552In all cases, there is a period, between 8:00 and 10:00 UTC, for both spring and 553summer, coinciding with the wind flow transition from night time land breeze to day 554time sea breeze, where the model captures very well the relative humidity observed.

In the third place, surface wind direction is rather well reproduced by the model 556for both inland and coastal stations, accounting for the daily regimes and cycles 557observed. Moreover, the onset of the wind flow transition from night time land breeze to 558day time sea breeze is also well captured by the model. In terms of surface wind speed, 559this magnitude is properly simulated by RAMS both at night and day time for inland 560stations in all seasons. In this case, greater differences between the modelled and 561observed results are found in the summer season. For coastal stations, the model shows 562greater differences, mainly at day time and during the summer. Thus, the model is too 563windy, specially over coastal stations, reducing the skill of the model in forecasting this 564magnitude. Nevertheless, the daily and day-to-day evolution is in general fairly captured 565by the model.

Finally, the precipitation forecasts are in general acceptable taking into account forthe restrictions and limitations in the initialization of an operational forecasting system forecasting system solves the one described here. However, the model shows a clear tendency to overestimate for the observations, as shown in the categorical statistics computed for the 24-h and the 6forth accumulated precipitation. It has been observed that this behaviour is more marked for for the first day of simulation, due to a significant over-prediction of the RAMS-simulated for the first causes for accumulated rainfall within the first 6-h interval (00:00-06:00 UTC). This result causes for simulation, and 574seems to be the reason for the higher differences found in the 24-h accumulated rainfall 575for this day compared to the second and third days of simulation.

As a final conclusion of the results shown in this work, it can be said that the 576 577 implementation of the RAMS model presented in this study as a forecasting tool within 578the Valencia Region works properly. The results found for air temperature, relative 579humidity, wind speed and direction, and precipitation are very similar as well for the 580three days of simulation, with the exception the first 6-h precipitation totals for the first 581day of simulation. However, some issues, as the initialization of the model, should be 582investigated more in depth to evaluate possible methodologies that improve the model 583 results. Besides, the performance of the radiative transfer parameterizations used in 584mesoscale models have a strong impact on the meteorological variables analysed within 585this paper. It is well known that radiation is one of the most important physical 586processes that drives the thermal circulations described. Thus, this information should 587be taken into account. Furthermore, the same model configuration has been maintained 588throughout the year. However, significant differences for the near-surface relative 589humidity have been observed between all seasons of the year separately, specially 590between the summer ans the winter. It is well known that the predominant 591meteorological situation during the summer over the area of study is associated with 592mesoscale circulations (Millán et al., 2005). However, during the winter more 593variability is observed in terms of the dominant atmospheric condition (Estrela et al., 5942010). As a consequence, the mentioned differences could also be related to a variance 595in the RAMS model performance under distinct weather and atmospheric conditions.

596 Although RAMS has been implemented for a concrete area within the Western 597Mediterranean Basin, due to its similar climate and physical characteristics, we strongly 598believe that the results found is this study could be projected as well to other areas in the 599east coast of the Iberian Peninsula. In addition, the results reproduced in the present 600paper are analogous to those found in other Mediterranean Regions, using the RAMS 601model (Pasqui et al., 2004; Federico, 2011), and using other real-time mesoscale models 602(Bartzokas et al., 2010). Likewise, considering other areas with Mediterranean-type 603climate regimes, it has been found that atmospheric humidity is the main cause of 604elevated minimum temperatures in the summer (Gershunov et al., 2009). In contrast, 605taking into account the temperature field within this season of the year, a cold bias was 606identified in RAMS simulations over east-central Florida (Case et al., 2002).

607 Considering the above mentioned points, it is the author's aim to continue the 608verification of this operational system by testing some improvements found in the 609model results in diagnostic studies, such as the analysis of the role of the convective 610parameterization in the precipitation forecasts.

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726

728Figure captions

729Fig. 1. RAMS model domain configuration and orography (m) of the Valencia Region 730(Domain 3) with the location of the representative coastal and inland CEAM weather 731stations.

732Fig. 2. Measured (continuous line) and simulated (discontinuous line) near-surface 733temperature (°C) and relative humidity (%) time series, for the different seasons of the 734year. Coastal stations: spring (a), summer (c), fall (e) and winter (g). Inland stations: 735spring (b), summer (d), fall (f) and winter (h).

736Fig. 3. Scatterplot of the simulated near-surface temperature (°C) versus the measured 737temperature (°C) at 05 and 13 UTC, for the different seasons of the year. Coastal 738stations: spring (a), summer (c), fall (e) and winter (g). Inland stations: spring (b), 739summer (d), fall (f) and winter (h).

740Fig 4. Same as Fig. 3, but for the near-surface relative humidity (%).

741Fig. 5. Same as Fig. 2, but for the near-surface wind speed (m/s) and direction (deg).

742Fig. 6. Same as Fig. 3, but for the near-surface wind speed (m/s).

743Fig. 7. Scatterplot of 24-h accumulated precipitation for the second day of simulation: 744spring (a), summer (b), fall (c) and winter (d).

745Fig. 8. Scatterplot of 6-h intervals accumulated precipitation for the second day of 746simulation. Spring: 00:00-06:00 UTC (a), 06:00-12:00 UTC (b), 12:00-18:00 UTC (c) 747and 18:00-24:00 UTC (d). Summer: 00:00-06:00 UTC (e), 06:00-12:00 UTC (f), 12:00-74818:00 UTC (g) and 18:00-24:00 UTC (h).

749Fig. 9. Same as Fig. 8, but for the fall: 00:00-06:00 UTC (a), 06:00-12:00 UTC (b), 75012:00-18:00 UTC (c) and 18:00-24:00 UTC (d), and the winter: 00:00-06:00 UTC (e), 75106:00-12:00 UTC (f), 12:00-18:00 UTC (g) and 18:00-24:00 UTC (h).

752Tables

-	Grid	nx	ny	nz	dx (m)	t (s)
-	1	83	58	24	48000	60
	2	146	94	24	12000	30
_	3	78	126	24	3000	10
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753Table 1. Rams model settings for the three simulation grids: number of grid points in 754the x, y and z directions (nx, ny and nz), horizontal grid spacing (dx) and timestep (t).

771Table 2. Model skill against surface observations for the first day of simulation and the 772different seasons of the year. Index of agreement, Bias and RMSE are included for the 773near-surface temperature (°C) and relative humidity (%). The "Night" value is that 774obtained at 05:00 UTC while the "Day" value corresponds to the one calculated at 13:00 775UTC. "All" value is the one taking into account all daily data.

		7	e	Rel	ative Humi	idity	
Station	Period	IoA	Bias	RMSE	IoA	Bias	RMSE
			Spi	ring			
All	All	0.9	1.0	4	0.8	-8	21
	Day	0.9	0.006	3	0.8	-3	18
	Night	0.8	1.6	4	0.6	-11	23
Coastal	All	0.9	0.4	3	0.8	-6	20
	Day	0.9	-0.4	3	0.8	-3	18
	Night	0.8	0.6	3	0.7	-8	22
Inland	All	0.9	1.3	4	0.8	-8	22
	Day	0.9	0.2	3	0.8	-2	17
	Night	0.8	2	4	0.5	-13	24
			Sun	nmer			
All	All	0.9	1.4	3	0.7	-15	23
	Day	0.9	0.17	3	0.7	-8	16
	Night	0.8	1.9	4	0.6	-17	25
Coastal	All	0.9	0.4	3	0.7	-12	20
	Day	0.9	-0.4	2	0.7	-9	16
	Night	0.8	0.7	2	0.6	-13	22
Inland	All	0.9	2	4	0.7	-16	24
	Day	0.9	0.4	3	0.7	-8	16
	Night	0.7	3	4	0.5	-20	30
			Fa	all			
All	All	0.9	0.2	3	0.8	-5	19
	Day	0.9	-1.1	3	0.8	-0.7	16
	Night	0.9	1.0	4	0.6	-7	21
Coastal	All	0.9	-0.5	3	0.8	-3	18
	Day	0.9	-1.6	3	0.8	-1.3	15
	Night	0.9	-0.04	3	0.7	-4	19
Inland	All	0.9	0.6	3	0.8	-6	20
	Day	0.9	-0.9	3	0.8	-0.4	16
	Night	0.9	1.5	4	0.6	-9	21
			Wi	nter			
All	All	0.8	0.4	4	0.7	-4	19
	Day	0.9	-0.9	3	0.8	-0.2	16
	Night	0.8	0.8	4	0.6	-6	20
Coastal	All	0.8	-0.3	4	0.8	-2	18
	Day	0.8	-1.4	4	0.8	0.7	17
	Night	0.8	-0.16	3	0.7	-3	18
Inland	All	0.8	0.7	4	0.7	-5	20
	Day	0.9	-0.7	3	0.8	-0.7	16
	Night	0.7	1.3	4	0.6	-7	21

781Table 3. Model skill against surface observations for the first day of simulation and the 782different seasons of the year. Index of agreement, Bias and RMSE are included for the 783near-surface wind speed (m/s). The VWD-RMSE statistic is included for the wind 784direction (m/s). The "Night" value is that obtained at 05:00 UTC while the "Day" 785values corresponds to the one computed at 13:00 UTC. "All" value is the one taking 786into account all daily data.

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			Wind Speed		VWD
		Sp	ring		
Station	Period	IoA	Bias	RMSE	RMSE
All	All	0.7	0.9	2	4
	Day	0.5	1.5	3	5
	Night	0.7	1.0	2	3
Coastal	All	0.7	1.1	2	4
	Day	0.5	1.9	3	5
	Night	0.6	1.2	2	3
Inland	All	0.7	0.8	2	4
	Day	0.5	1.3	3	5
	Night	0.7	0.9	2	3
		Sun	nmer		
Station	Period	IoA	Bias	RMSE	RMSE
All	All	0.7	1.5	2	4
	Day	0.4	3	3	5
	Night	0.5	1.1	1.9	3
Coastal	All	0.7	1.5	2	4
	Day	0.4	3	3	5
	Night	0.5	0.9	1.8	3
Inland	All	0.7	1.5	2	4
	Day	0.4	3	3	5
	Night	0.5	1.2	2	3
		F	all		
Station	Period	IoA	Bias	RMSE	RMSE
All	All	0.7	1.0	2	4
	Day	0.6	1.5	3	4
	Night	0.7	1.1	2	3
Coastal	All	0.7	1.2	2	3
	Day	0.5	2	3	4
	Night	0.6	1.1	2	3
Inland	All	0.7	0.9	2	4
	Day	0.6	1.3	3	4
	Night	0.7	1.1	2	3
		Wi	nter		
Station	Period	IoA	Bias	RMSE	RMSE
All	All	0.7	0.5	2	4
	Day	0.7	0.17	2	4
	Night	0.7	0.8	2	4
Coastal	All	0.7	0.9	2	4
	Day	0.7	0.5	2	4
	Night	0.6	1.2	3	4
Inland	All	0.7	-0.3	2	4
	Day	0.7	0.02	2	4
	Night	0.7	0.6	2	4

	Categorical Scores				Daily	(24-h)			
			Spr	ing			Sum	mer	
		$\geq 2mm$	$\geq 8 mm$	≥ 15mm	\geq 30mm	$\geq 2mm$	$\geq 8 mm$	≥ 15mm	≥ 30mm
	AC	0.8	0.9	0.9	1.0	0.9	1.0	1.0	1.0
	Bias	1.5	1.9	2.4	4	1.0	1.2	2	3
	POD	0.6	0.4	0.2	0.1	0.2	0.15	0.05	0.07
	FAR	0.6	0.8	0.9	1.0	0.8	0.9	1.0	1.0
	CSI	0.3	0.18	0.07	0.03	0.13	0.08	0.016	0.019
	HSS	0.4	0.3	0.11	0.04	0.2	0.12	0.02	0.03
			Fa	ıll			Win	nter	
	AC	0.8	0.9	0.9	1.0	0.8	0.9	1.0	1.0
	Bias	1.2	1.1	1.1	1.1	1.4	1.7	1.7	1.5
	POD	0.5	0.3	0.2	0.10	0.6	0.4	0.3	0.2
	FAR	0.6	0.7	0.8	0.9	0.6	0.7	0.8	0.9
	CSI	0.3	0.18	0.11	0.05	0.3	0.2	0.11	0.09
	HSS	0.4	0.3	0.17	0.08	0.4	0.3	0.18	0.16
818 819 820 821 822 823 824 825 826 827 828 829 830 831 832 833 834 835 836 837 838									

815Table 4. Categorical statistics for 24-h accumulated precipitation for all seasons of the 816year and the second day of simulation.817_____

	Categorical Scores	First 6	-h interval (00:00-06:00 U	JTC) accum	ulated precip	oitation
			Spring			Summer	
		$\geq 2mm$	≥ 8 mm	$\geq 15 \text{mm}$	$\geq 2mm$	≥ 8 mm	\geq 15mm
	AC	1.0	1.0	1.0	1.0	1.0	-
	Bias	1.4	1.8	1.4	0.5	0.12	-
	POD	0.4	0.18	0	0	0	-
	FAR	0.7	0.9	1.0	1.0	1.0	-
	CSI	0.2	0.07	0.0	0	0	-
	HSS	0.3	0.13	-0.0014	0.006	-0.0006	-
			Fall			Winter	
	AC	0.9	1.0	1.0	0.9	1.0	1.0
	Bias	1.1	0.9	0.5	1.5	2	3.6
	POD	0.3	0.02	0	0.4	0.18	0.2
	FAR	0.8	1.0	1.0	0.8	0.9	0.9
	CSI	0.14	0.011	0	0.2	0.06	0.05
	HSS	0.2	0.008	-0.006	0.3	0.11	0.09
842 843 844 845 846 847 848 849 850 851 852 853 854 855 856 857 858 857 858 859							

863Table 6. Categorical statistics for the second 6-hour interval (06:00-12:00 UTC) 864accumulated precipitation for all seasons of the year and the second day of simulation.

Categorio Scores	cal Second	6-h interval	(06:00-12:00	UTC) accur	nulated prec	ipitation		
		Spring		Summer				
	$\geq 2mm$	$\geq 8 \text{mm}$	\geq 15mm	$\geq 2mm$	≥ 8 mm	$\geq 15 \text{mm}$		
AC	0.9	1.0	1.0	1.0	1.0	1.0		
Bias	1.6	1.4	3	0.6	0.8	1.6		
POD	0.3	0.03	0	0.1	0	0		
FAR	0.8	1.0	1.0	0.8	1.0	1.0		
CSI	0.13	0.014	0	0.07	0	0		
HSS	0.2	0.02	-0.002	0.12	-0.003	-0.0011		
		Fall			Winter			
AC	0.9	1.0	1.0	0.9	1.0	1.0		
Bias	1.1	1.0	0.6	1.6	1.4	2		
POD	0.4	0.17	0.13	0.3	0.2	0.17		
FAR	0.7	0.8	0.8	0.8	0.8	0.9		
CSI	0.2	0.09	0.09	0.15	0.11	0.06		
HSS	0.3	0.16	0.15	0.2	0.2	0.10		
360 367 368 369 370 371 372 373 374 375 376 377 378 379 380 381								
882 883								

887Table 7. Categorical statistics for the third 6-hour interval (12:00-18:00 UTC) 888accumulated precipitation for all seasons of the year and the second day of simulation. 889

Categorical Scores	Third 6	5-h interval ([12:00-18:00]	-18:00 UTC) accumulated precipitation							
		Spring		Summer							
	$\geq 2mm$	≥ 8 mm	\geq 15mm	$\geq 2mm$	≥ 8 mm	≥15mm					
AC	0.9	1.0	1.0	0.9	1.0	1.0					
Bias	1.8	2	3	1.4	2	4					
POD	0.4	0.18	0	0.2	0.18	0.14					
FAR	0.8	0.9	1.0	0.8	0.9	1.0					
CSI	0.17	0.06	0	0.10	0.06	0.03					
HSS	0.2	0.10	-0.009	0.16	0.10	0.05					
		Fall			Winter						
AC	0.9	1.0	1.0	0.9	1.0	1.0					
Bias	1.3	1.2	1.5	1.4	1.6	1.5					
POD	0.3	0.16	0.08	0.3	0.06	0					
FAR	0.8	0.9	0.9	0.8	1.0	1.0					
CSI	0.13	0.08	0.03	0.14	0.02	0					
HSS	0.18	0.12	0.05	0.2	0.04	-0.004					

912Table	8.	Categorical	statistics	for	the	fourth	6-hour	interval	(18:00-24:00	UTC)
913accum	ulat	ted precipitati	ion for all	seas	ons c	of the ye	ear and the	he second	day of simula	tion.
914										

Categorical Scores	Fourth	6-h interval	(18:00-24:00	UTC) accur	nulated prec	ipitation		
		Spring		Summ				
	$\geq 2mm$	≥ 8 mm	$\geq 15 \text{mm}$	$\geq 2mm$	≥ 8 mm	≥15mm		
AC	0.9	1.0	1.0	1.0	1.0	1.0		
Bias	1.8	1.6	3	0.8	1.0	2		
POD	0.3	0.07	0	0.08	0	0		
FAR	0.8	1.0	1.0	0.9	1.0	1.0		
CSI	0.13	0.03	0	0.05	0	0		
HSS	0.17	0.04	-0.004	0.07	-0.005	-0.002		
		Fall			Winter			
AC	0.9	1.0	1.0	0.9	1.0	1.0		
Bias	1.5	1.1	0.9	1.4	0.8	1.0		
POD	0.15	0	0	0.4	0.11	0.11		
FAR	0.9	1.0	1.0	0.7	0.9	0.9		
CSI	0.07	0	0	0.2	0.06	0.06		
HSS	0.08	-0.017	-0.008	0.3	0.11	0.11		
6 7 8 9 0 1 2 3 4 5 6 7 8								
8 9 0 1 2 3								





Figure 1









Figure 4





Figure 6



953

Figure 7



Figure 8



Figure 9