Medicane Ianos 17 September 2020 in Ionian Sea (dcmdb: Ianos_2020)

Case description

Medicane Ianos had a behaviour similar to mature tropical cyclones, including the upwelling associated with cyclone winds.

More info in DE_330_M330.5.3.1_202210_MilestoneNote_v2.

Model configuration:

- On-Demand DT prototype 0.4.0 using HARMONIE-AROME configuration based on CY46h1. Runs on ECMWF-ATOS at 500 m resolution (1536x1536, 65L). Initial and boundary conditions from IFS HRES.

Reference simulation:

- Global DT (expver: ht3e)

Dates run (OD-DT): 2020091400 to 2020091818, each 6 hours.

Output (OD-DT):

- ectmp:/sp0c/deode/CY46h1_HARMONIE_AROME_IA2X/
- /ec/res4/scratch/sp0c/deode/CY46h1_HARMONIE_AROME_I02X/

Observations used for spatial verification: IMERG (1-hour accumulated precipitation) and SEVIRI (brightness temperature from meteosat 09 channel 9)

Verification/Assessment/Analysis: Three initializations are available for the DT with forecasts up to H+48, so only 2020091412, 2020091500 and 2020091600 have been used for comparison. Two domains have been necessary to verify at sub-kilometer scale with the high-resolution prototype. The analysis focuses on 15-17 September, both included. On 15 September (initial stage of medicane), the precipitation field affects northern Libya and the Gulf of Sidra. During day 16, the cyclone evolves into a powerful medicane on day 17, progressively affecting Greece [1]. Figure 1 shows the accumulated precipitation during September 16 and 17 derived from the IMERG satellite (middle panel) and the 16 September 00 UTC initializations of the experiments: DT (left panel) and OD-DT (right panel). From these plots we can see that both models underestimate the satellite-derived precipitation field, especially in coastal areas.

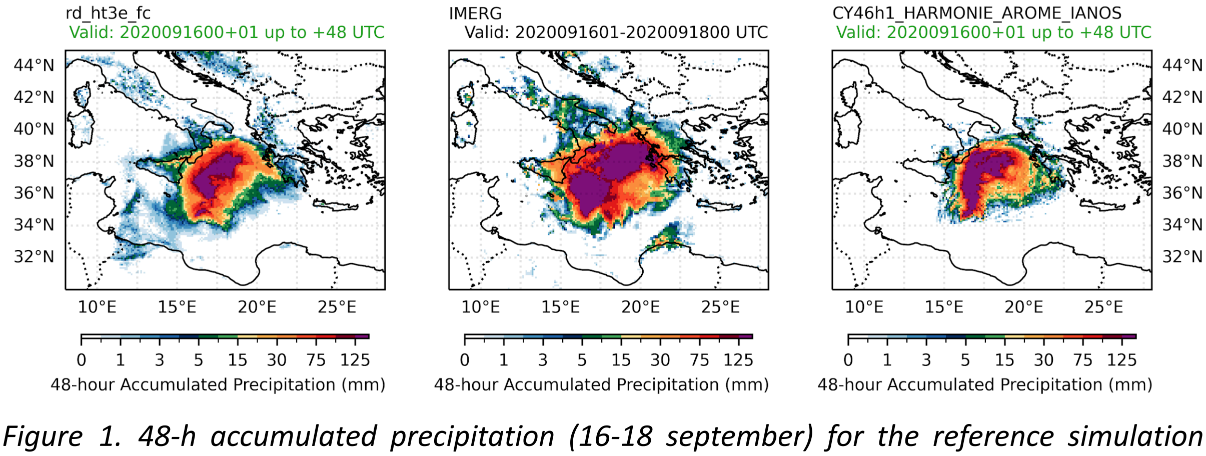

Figure 1. 48-h accumulated precipitation (16-18 september) for the reference simulation (DT), the observations (IMERG satellite) and the OD-DT (HARMONIE-AROME version).

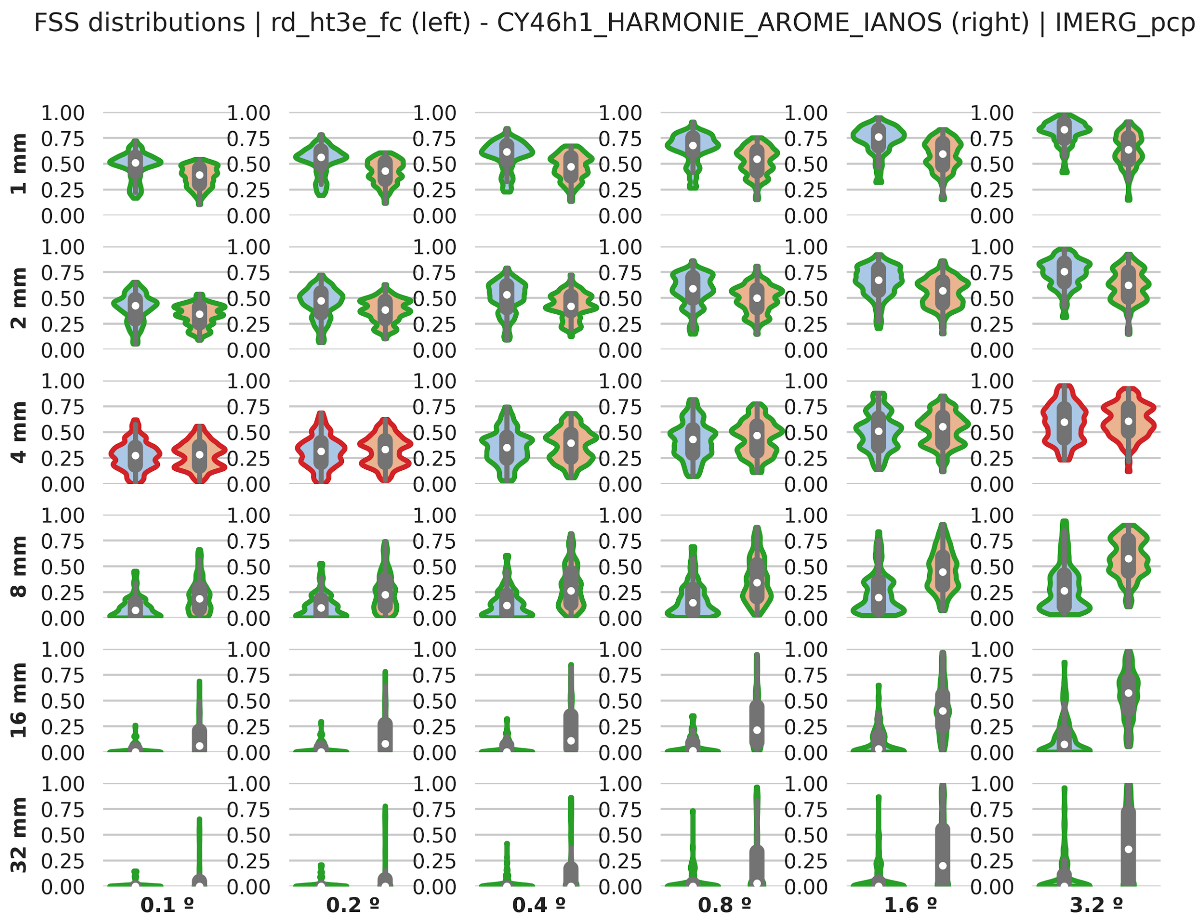

Figure 2. Violin plots of Fractional Skill Score (FSS) for several hourly cumulative precipitation thresholds (rows) and spatial scales (columns). Each panel shows the FSS distribution for DT (left, blue) and OD-DT (right, orange). Green and red edges represent whether the two distributions pass the Wilcoxon signed-rank test (p-Value less than 0.05) or not, respectively.

In order to quantify spatial accuracy of the forecasts, the Fractional Skill Score (FSS) is computed for the common ranges between the reference model and the sub-kilometer scale prototype, i.e., a total of 112 time steps have been verified. The verification domain has an approximate extent of 265000 km^2 and is centered on the event, following the cyclone track. Figure 2 shows the FSS distributions of the two experiments for several hourly precipitation thresholds and several spatial scales. Although the FSS values increase with spatial scale, the comparison between the two experiments and the main results are not sensitive to this parameter. However, two scenarios can be distinguished according to the precipitation thresholds. For thresholds below 4 mm/h, DT obtains higher FSS values than OD-DT. On the other hand, values higher than 4 mm/h are better represented in the sub-kilometer scale experiment, especially at large spatial scales, because the extreme values are not represented by the DT and the increase of the scale does not translate into a higher spatial accuracy.

Figure 3 shows the FSS distributions obtained for the brightness temperatures from both experiments. In this case, both models obtain similar FSS, with similar median values of the distributions (white points), especially for low values (in absolute value) and large spatial scales. However, these distributions have a smaller range, i.e. smaller dispersion, in the sub-kilometer scale experiment. As in the case of hourly precipitation, a larger difference between experiments is obtained for extreme values, i.e., for brightness temperature values below -50 ºC.

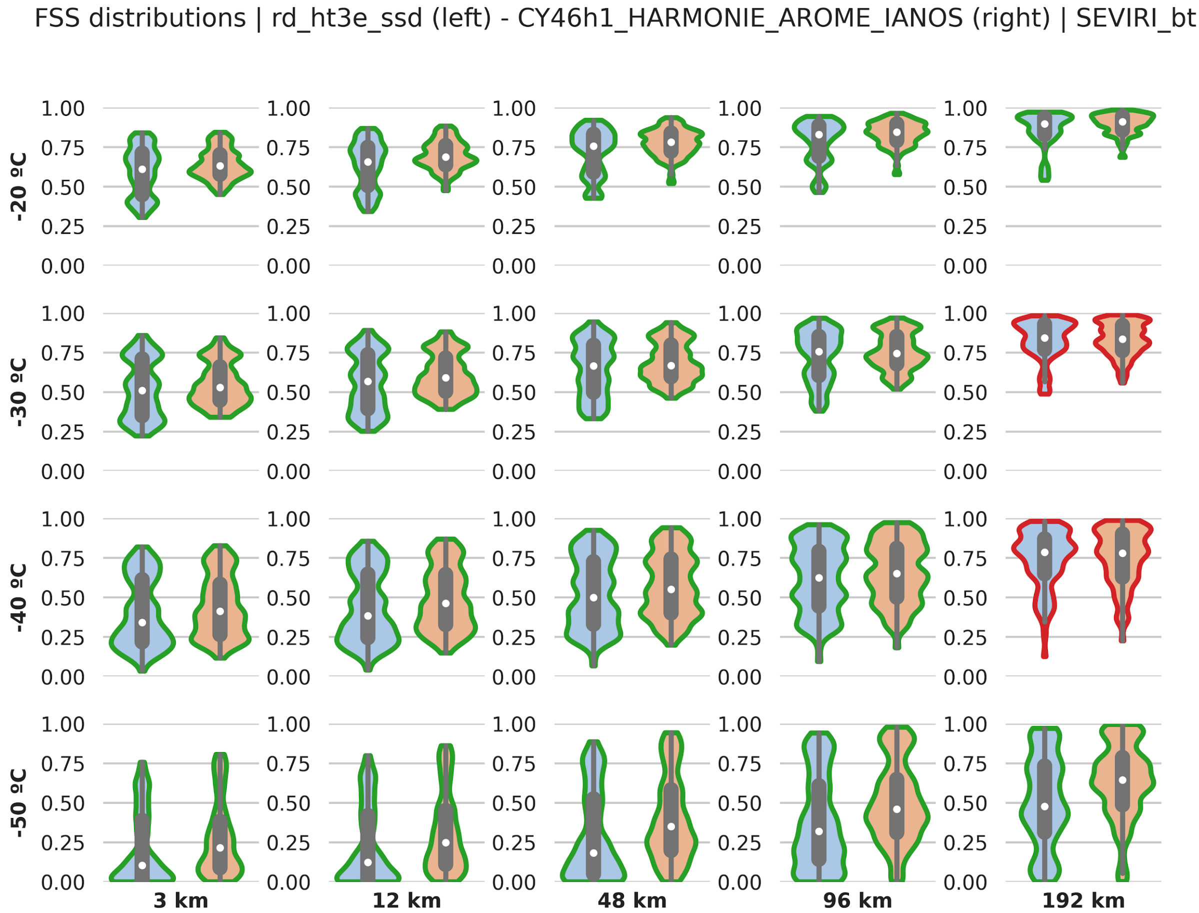

Figure 3. Same as Figure 2 but for brightness temperature.

Another metric that allows us to quantify spatial accuracy is SAL. Figure 4 shows the SAL plots obtained for the reference experiment (left panel) and the OD-DT (right panel). For object detection, the default parameters of the “pysteps” Python module [2] have been used, along with a minimum size of 20 pixels and a threshold value of $R = f*P_{95}$, where $f = 0.5$ is the factor chosen to set the threshold for objects with high hourly precipitation values and P_{95} is the 95th percentile of the values contained within the verification domain. Both models underestimate the precipitation field, i.e. negative amplitude values, because the satellite represents a larger precipitation field compared to the more localized precipitation fields represented by the models. This detection of larger objects in the observations is also evidenced by an overall negative structure value for both models. However, larger objects (higher S values) do not result into less underestimation, as more extreme values are found within the verification domain for the hectometer scale experiment. Some of the verified instants for the reference model achieve a positive structure value causing a larger spread of this value. As for the localization value of these objects, similar values are found for both models.

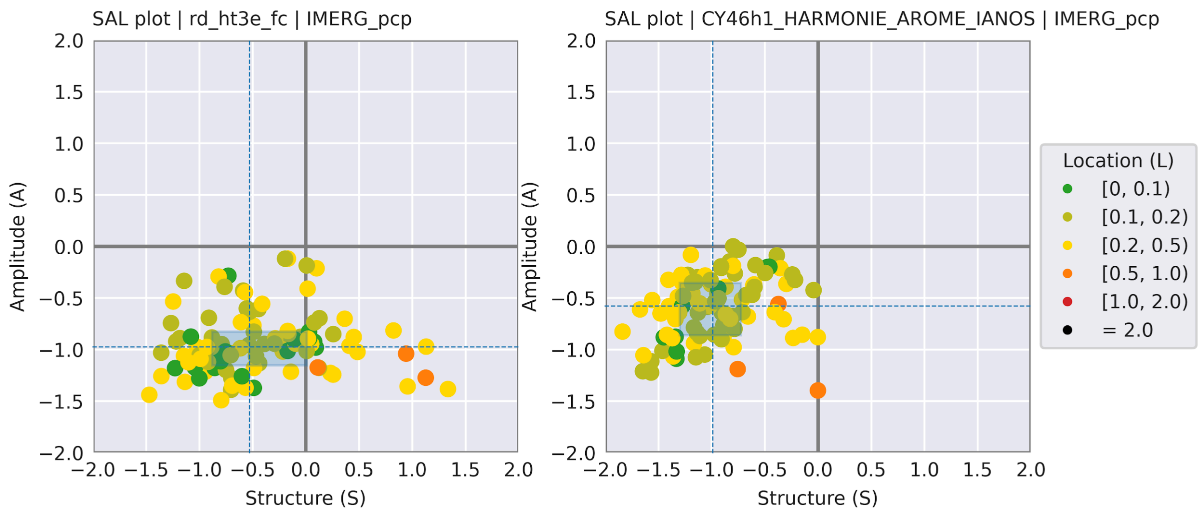

Figure 4. Salt-plot for the IFS-HRES (left panel) and the DEODE prototype (right panel). Each point represents a verified time step. Blue square shows the interquartile range of the amplitude and structure values contained in each of the panels. Dotted blue lines represent the median of these values.

In the case of brightness temperature (Figure 5), the same object detection parameters have been employed although a minimum size of 50 pixels has been used due to the higher spatial resolution of SEVIRI. Both models achieve similar values. In this case, the dispersion of the amplitude and structure values is much smaller in both experiments and they are close to the origin of coordinates, achieving a good representation of the brightness temperature along the event. Similar values for the location of the objects are achieved by both models.

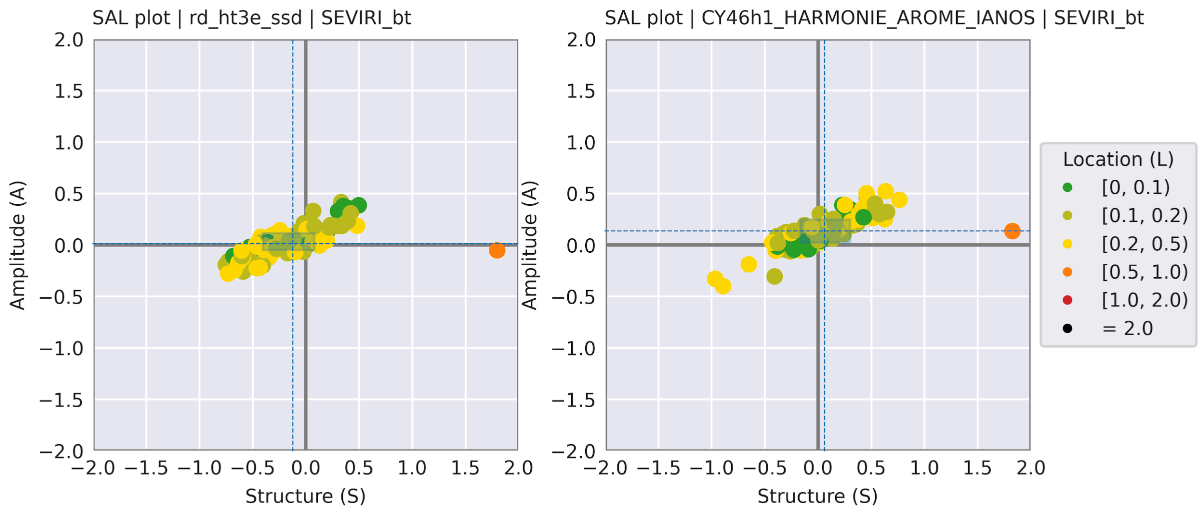

Figure 5. Same as Figure 4 but for brightness temperature.

Sensitive analysis: An additional experiment has been performed. In this case, the same version of the prototype has been coupled to DT (expver: i1vt) in two initialisations: 2020091500 and 2020091506. A total of 46 time steps (valid time up to 20200916 02 UTC) have been spatially verified and compared. Very similar results are obtained for both experiments (especially in the SAL values), both in precipitation and brightness temperature. Figure 6 shows the FSS distributions for several hourly precipitation thresholds and spatial scales obtained by the prototype when coupled to HRES-IFS and DT. These FSS distributions are very similar between the two experiments although slightly higher scores are obtained when HRES-IFS is employed as boundary conditions.

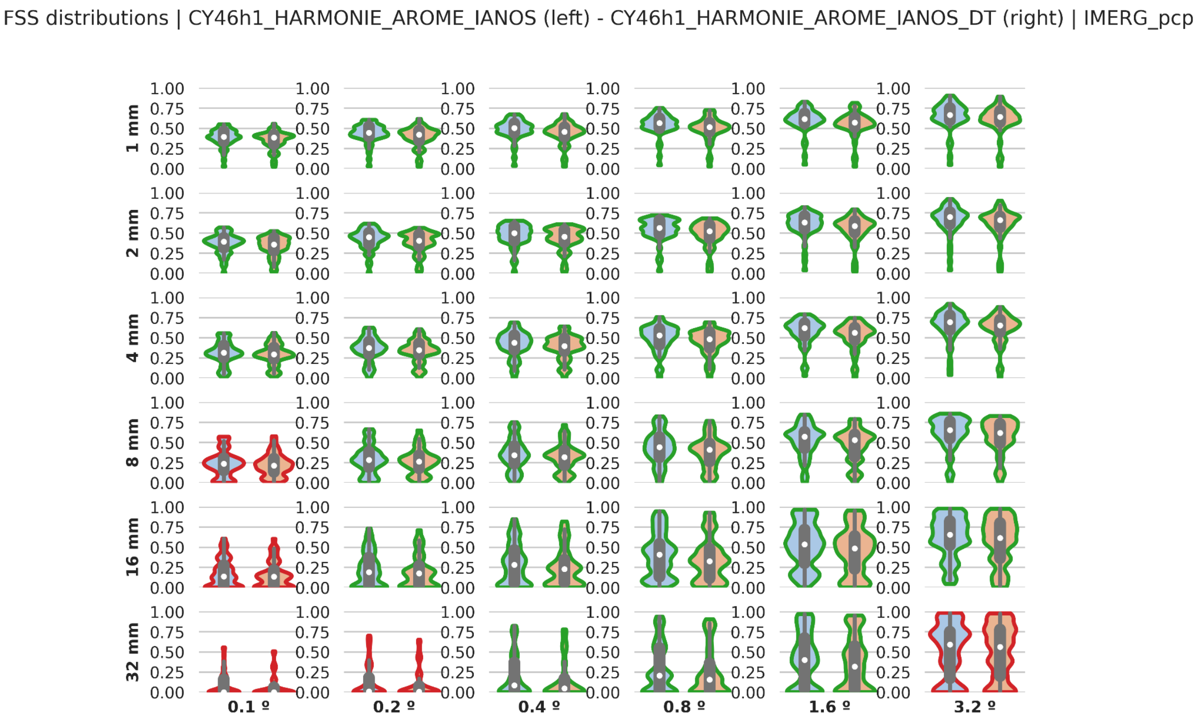

Figure 6. Same as Figure 2 but for OD-DT coupled to HRES-IFS (left, blue) and OD-DT coupled to global DT (right, orange).

Summary:

Similar results have been found for both experiments, especially for brightness temperature. This variable yields higher scores than hourly precipitation. The brightness temperature is represented as practically unbiased and at many time steps high values of FSS and values close to 0 in SAL are obtained. The precipitation field is underestimated by both models, with higher precipitation cores less extensive than those derived from the satellite. The sub-kilometer scale experiment is able to represent high precipitation values achieving higher scores for high precipitation thresholds than the reference experiment. No huge differences have been found when modifying the boundary conditions of the LAM although slightly better scores are found when the OD-DT is coupled to HRES-IFS.

References

[1] Lagouvardos, K., Karagiannidis, A., Dafis, S., Kalimeris, A., & Kotroni, V. (2022). Ianos—A hurricane in the Mediterranean. *Bulletin of the American Meteorological Society*, *103*(6), E1621-E1636.

[2] Pulkkinen, S., Nerini, D., Pérez Hortal, A. A., Velasco-Forero, C., Seed, A., Germann, U., & Foresti, L. (2019). Pysteps: An open-source Python library for probabilistic precipitation nowcasting (v1. 0). *Geoscientific Model Development*, *12*(10), 4185-4219.