A comparison of deep convection detection algorithms based on thresholding techniques applied to Meteosat-11 satellite data for European Russia

Shishov A.E.
The Hydrometcentre of Russia, 123376 Moscow, Russia, B. Predtechensky per.
shandruha@gmail.com

Data from the infrared channels of the Spinning Enhanced Visible and Infrared Imager (SEVIRI) provides a convenient satellite way of detecting and analyzing deep convective clouds during both daytime and nighttime. It is the primary instrument of the geostationary satellite Meteosat-11, which has a sampling distance of 3-5 km depending on the longitude and latitude of the observed area, and a temporal resolution of 15 min. Motivated by the problem of forecasting hazards for aviation, this study presents a comparison of four different detection algorithms designed to detect deep convective clouds, which will be referred to as convective objects (COs).

The quality of each algorithm is evaluated on data for the period July 14-16, 2020. The analysis was conducted using the measurements of brightness temperature in the following infrared window channels: 10.8 μm - $T_{10.8}$, 6.2 $\mu m - T_{6.2}$, 7.3 $\mu m - T_{7.3}$. The region of interest was confined between 30° and 70° latitude, 20° and 75° longitude. The dataset consisted of 288 observations, each one being a set of three images (one image per channel).

Algorithm 1. Thresholding criteria included critical brightness temperature values - that is, pixels with brightness temperature $T_{10.8}$ below 233 K as well as temperature differences $(T_{6.2} - T_{10.8})$ and $(T_{6.2} - T_{7.3})$ above -10 and -4 K correspondingly were selected [1]. Furthermore, since the shape of deep convective cloud boundary as viewed from outer space is typically convex [2], we also used an additional convexity criterion based on solidity index [3]: the ratio of CO area to the area of its convex hull must be above 0.7.

Algorithm 2. Assuming that the temperature of a deep convective cloud top is at least as low as 220 K [4], we added one more criterion to the ones mentioned before: a candidate object must have at least one pixel with brightness temperature $T_{10.8}$ below 220 K in order to be considered a CO.

Algorithm 3. The previous algorithm was augmented with the variable thresholding technique applied to IR 10.8 channel: if a candidate object did not meet the convexity criterion mentioned above, the critical value was iteratively lowered (which caused the object to shrink in size and change in shape) until it did or until a maximum number of iterations was reached.

Algorithm 4. An approach proposed by K.M. Bedka [5]. It takes into account not only the brightness temperature $T_{10.8}$ at a given pixel, but also the mean of its neighbours and standard deviation from that mean.

The detections were validated using the distributions of two parameters: CO lifetime defined as the number of successive steps at which the same CO was detected (converted to time in minutes through multiplication by 15); and CO maximum area defined as the maximum size in km^2 reached by that CO during its lifetime (see Table 1). The analysis revealed that Algorithm 1 detected a large number of small short-lived COs, i.e. those with lifetimes less than one hour and areas less than 310 km^2. Hence, it is applicable to the task of detecting weak convection as it occurs frequently under unstable atmospheric conditions. In the meanwhile, the stricter criteria of Algorithm 2 enabled it to detect significantly fewer small short-lived COs, since the tops of the most of them were warmer than the defined threshold of 220 K. As a result, the detected objects were more powerful, had a bigger size and a longer lifetime. COs detected by Algorithm 3 were more numerous due to the variable thresholding technique, which increased the chances of an object to meet the convexity criterion. Algorithm 4 distinguished itself by the greatest number of detected COs of all sizes and lifetimes. It can extract valuable information from IR 10.8 channel alone as it considers spatial brightness temperature gradients. However, among the detected COs there were too many small objects that lived for less than one hour as well as some big ones with distorted contours (see Figure 1). Given that images studied by Bedka had a higher resolution, we conclude that this algorithm requires calibration to yield adequate results on our data.

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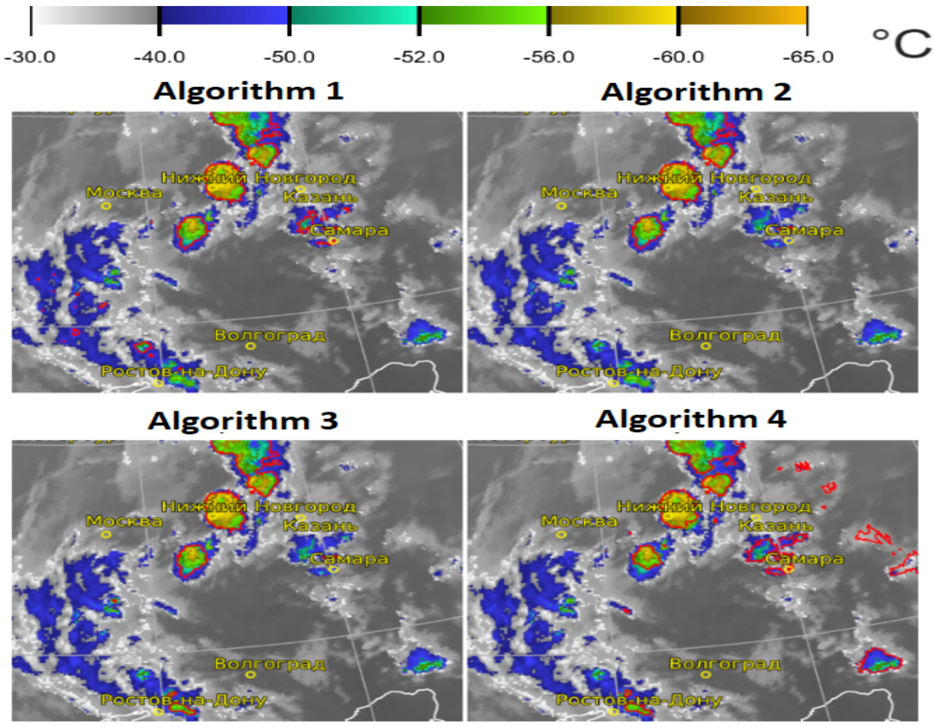

Figure 1. Examples of contours (in red) of COs detected by the algorithms, color-enhanced IR 10.8 channel data as a background, UTC 00:00 2020-07-14

Table 1. Frequency of COs detected by the algorithms, grouped by lifetime and area

Area (km^2)	Lifetime (hours)	Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4
25-80	< 1	7492	415	1103	11151
	1-6	10	1	2	9
80-310	< 1	2217	108	263	5642
	1-6	3	1	1	89
310-700	< 1	729	77	222	1891
	1-6	9	6	8	110
	6-12	0	0	0	1
700-100000	< 1	540	195	260	1110
	1-6	84	37	58	369
	6-12	4	4	5	34
	12+	0	0	0	4
100000-200000	6-12	1	1	0	0
	12+	0	0	1	0

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