



C³ONTEXT: a Common Consensus on Convective OrgaNizaTion during the EUREC⁴A eXperiment

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Abstract. The C³ONTEXT (a Common Consensus on Convective OrgaNizaTion during the EUREC⁴A eXperiment) dataset is presented as an overview of the mesoscale cloud patterns identified during the EUREC⁴A (Elucidating the role of clouds–circulation coupling in climate) field campaign in early 2020. Based on infrared and visible satellite images, 50 researchers of the EUREC⁴A science team manually identified the four prevailing mesoscale patterns of shallow convection observed by Stevens et al. (2020). The common consensus on the observed mesoscale cloud patterns emerging from these manual classifications is presented. It builds the basis for future studies and reduces the subjective nature of these visually defined cloud patterns. This consensus makes it possible to contextualize the measurements of the EUREC⁴A field campaign and interpret them in the mesoscale setting. Commonly used approaches to capture the mesoscale patterns are computed for comparison and show good agreement with the manual classifications. All four patterns as classified by Stevens et al. (2020) were present in January–February 2020, although not all were dominant during the observing period of EUREC⁴A. Supplemental classifications of storm-resolving simulations suggest that the latter have a limited ability to replicate the observed cloud patterns and require further research.

The full dataset including post-processed datasets for easier usage are openly available at the Zenodo archive at <https://doi.org/10.5281/zenodo.5979718> (Schulz, 2022a).

1 Introduction

Clouds are often clustered. Examples of larger clusters are squall lines and the intertropical convergence zone. But also much smaller clouds like shallow trade wind cumuli are often seen clustered on a scale of several hundred kilometers. The understanding of these mesoscale patterns of shallow convection is still sparse. However, the ubiquity of these clouds and their reoccurring structure suggest that they play an important role in determining the radiative effects of the trade wind regimes (Bony et al., 2020). The EUREC⁴A (Elucidating the role of clouds–circulation coupling in climate) field campaign addresses among others, the question of which processes are at play that change the mesoscale appearance of shallow convection. Prior to the campaign, studies concentrated on the classification of mesoscale patterns based on satellite images by visual inspection (Stevens et al., 2020),

rule-based algorithms (Bony et al., 2020; Janssens et al., 2021), supervised neural networks (Rasp et al., 2020) and unsupervised neural networks (Denby, 2020). Most of these methods focus on four specific mesoscale cloud patterns that have been identified as commonly occurring in the North Atlantic downwind trades (Stevens et al., 2020). An overview of these four patterns which are named by their visual impressions as *sugar*, *gravel*, *flowers* and *fish* is given in Fig. 1.

These efforts show that the categorization of the mesoscale patterns is an elementary step in acquiring further knowledge about the cloud processes in the downstream trades; 50 scientists from 15 research institutes who were involved in the EUREC⁴A field campaign in January–February 2020 therefore participated in a joint online classification event. The results of this classification event are presented here. Due to the high attendance, the presented dataset can be interpreted as the common judgment of the EUREC⁴A science

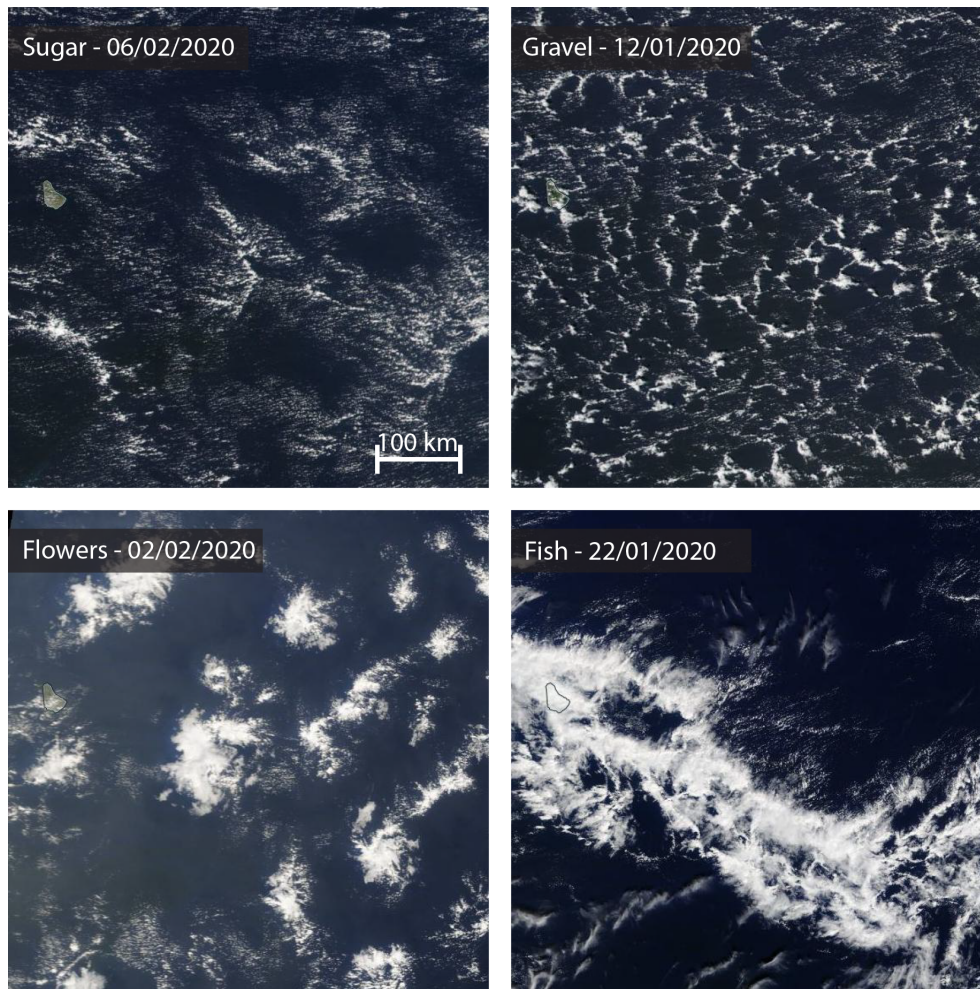


Figure 1. Four classes of mesoscale patterns of shallow convection have been labeled by 50 scientists in satellite images of January and February 2020. An example of each of these classes is shown based on the reflectance measurements of the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite (sugar and gravel) and the Visible Infrared Imaging Radiometer Suite (VIIRS) on board the Suomi National Polar-orbiting Partnership (NPP) satellite (flowers and fish). Example images provided by NASA Worldview.

team on the mesoscale patterns of shallow convection in the wider trades during EUREC⁴A. The studied domain of 5–20° N, 62–40° W contains the entire research area, including both the *Tradewind Alley* in the north (12.5–14.5° N) and the *Boulevard des Tourbillons* close to the coast of South America (Stevens et al., 2021). This dataset therefore allows for consistently communicating about the otherwise subjectively defined patterns and puts the measurements taken during EUREC⁴A into their mesoscale context to advance the process understanding of shallow convection in the trades. The need for a better process understanding is highlighted by a supplemental classification of storm-resolving simulations covering the same time period.

The paper is structured as follows: the dataset and its collection are described in Sect. 2. Potential use cases are described in Sect. 3. In Sect. 4 additional classification methods that are able to detect the four mesoscale patterns are

applied to the EUREC⁴A time period and compared to the manual classifications described in this paper. We conclude with Sect. 6.

2 Data description and development

The manual classifications were gathered through the online platform <https://www.zooniverse.org/> (last access: 1 July 2020), which has already been successfully used in an earlier project by Rasp et al. (2020). The platform makes it possible to crowdsource labels for, e.g., machine learning projects. Additional workflows can be defined to separate different image sources or to separate, for example, labels made during a practice run from those that belong to the actual classification. The former allowed everyone to familiarize themselves with the <https://www.zooniverse.org/> platform without influencing the results.

For this dataset, we defined three workflows. Two workflows are based on satellite observations. The first one is based on the visible channels of both the GOES-16 (Geostationary Operational Environmental Satellite) ABI (Advanced Baseline Imager) and MODIS on board the Aqua and Terra satellites and is called EUREC⁴A VIS. The second one is based on the “clean” infrared channel (channel 13) of GOES-16 ABI only (EUREC⁴A IR). To test how well storm-resolving simulations are able to reproduce the observed patterns, we included another workflow, EUREC⁴A ICON, which is based on ICON (ICOSahedral Nonhydrostatic) storm-resolving simulations covering the EUREC⁴A time period. The simulation has a grid spacing of 1.25 km and was initialized daily by the European Centre for Medium-Range Weather Forecasts Integrated Forecasting System (ECMWF IFS) and forced hourly. Each run is 48 h long. The first 24 h were discarded to allow for spin-up.

To visualize the simulation output, we calculated a pseudo-albedo α by following the approximation of Zhang et al. (2005):

$$\tau = 0.19 \cdot \text{LWP}^{\frac{5}{6}} \cdot N^{\frac{1}{3}} \quad (1)$$

$$\alpha = \frac{\tau}{6.8 + \tau}, \quad (2)$$

where τ is the optical depth, LWP is the liquid water vapor path and N is an assumed cloud droplet number density. Here a number density of 70 cm^{-3} is used, which is at the lower end of the observed concentrations (Siebert et al., 2013).

All workflows are further described in Table 1.

On 24 March 2020 the international, virtual classification event was hosted with 50 scientists from 15 institutes participating in the creation of the pattern classifications. For a full day the participants classified patterns of shallow trade wind convection by labeling, i.e., drawing rectangles of variable sizes around, the four common types: sugar, gravel, flowers and fish (Stevens et al., 2020).

In the end, over 12 500 labels were gathered. The observational workflows got the majority of the labels (see Fig. 2) because the identification of the patterns in the model simulation was too demanding. The cloud features in the simulations had too little similarity with those found in nature. By comparing the distribution of labels in the individual workflows, Fig. 2 reveals that sugar was disproportionately rarely identified in the ICON simulations. The largest feature, like fish, however, has been identified more often. This supports the assumption that larger features are better reproduced in storm-resolving simulations than features of smaller scales, like sugar.

Because all users have familiarity with the patterns either by previous work and/or being involved in the classification event of Rasp et al. (2020), it can be assumed that the labels are of high quality. In addition, they were trained immediately before starting the classification through an online presentation to get familiar with the labeling in-

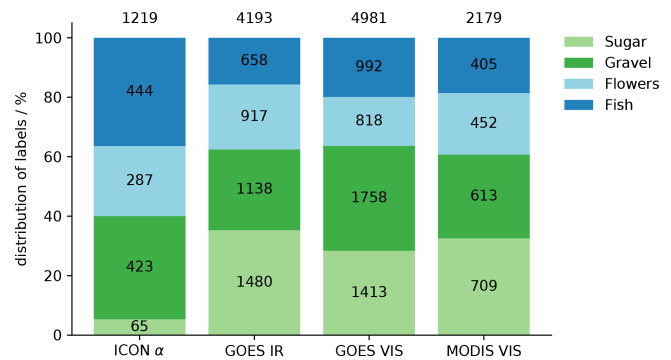


Figure 2. Distribution of labels by data source. The relative distribution is shown on the y axis, while the absolute number of labels is indicated within each bar. The total number of labels per workflow is shown on the top of each bar.

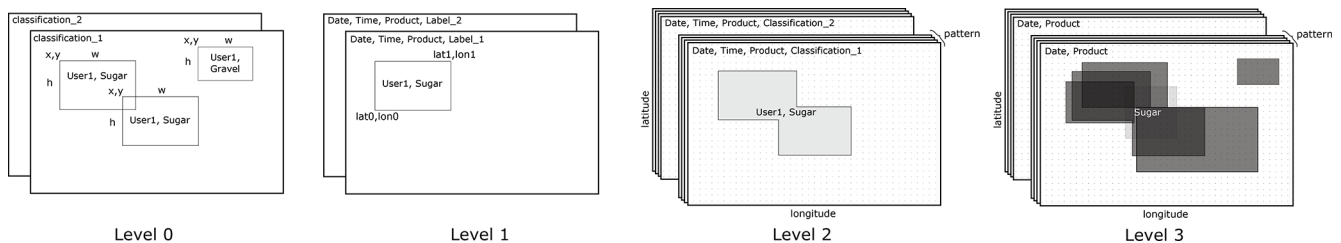
terface on <https://www.zooniverse.org/> and to once more refresh the different mesoscale cloud pattern categories. Compared to Rasp et al. (2020), where the focus has been to classify as many diverse cloud scenes as possible to capture nature’s variability and thus serve as a better machine learning dataset, the aim for this dataset is to create a common classification dataset for the EUREC⁴A time period that participating scientists agree on and can directly be used in further studies. Therefore, the temporal frequency has been increased from daily cloud scenes to 2-hourly cloud scenes to reflect also the changes on the sub-daily scale such as those identified by Vial et al. (2021). Due to this design difference, a single day is now on average classified 20 times in case of the visible workflow instead of just about 6 (3 per each day-time Aqua/Terra satellite overpass) as in Rasp et al. (2020). Each individual image is however still viewed about 3 times.

After the joint classification event, over 12 500 labels were processed to make them more user friendly, especially because the raw data miss temporal and geospatial information. The processing steps with the intermediate products are illustrated in Fig. 3 and described as follows:

- *Level 0.* The level 0 dataset consists of the raw data output and originates from the Zooniverse platform. It consists of CSV (comma-separated values) files that contain entries for each workflow, image (subject) and classification including technical details like the time spent on drawing a specific label. Labels are given by their origin (x, y) and their height (h) and width (w) given in pixel coordinates.
- *Level 1.* The level 1 dataset is further processed and combines the information distributed over the level 0 dataset files. It contains each label as a separate entry and contains information about the classified object, the user, and the geographical and Cartesian coordinates of the label. This product is saved in a netCDF (Network Common Data Form) file.

Table 1. Description of data sources used to create the images of the classification workflows.

	EUREC ⁴ A VIS		EUREC ⁴ A IR	EUREC ⁴ A ICON
	MODIS (Terra/Aqua)	ABI (GOES-16)	ABI (GOES-16)	
Domain	5–20° N, 62–40° W			5–20° N, 62–44° W
Period	7 Jan 2020–22 Feb 2020			16 Jan 2020–20 Feb 2020
Resolution	~ 1 km			~ 2 km
(shown)	2-hourly, 12:00–20:00 UTC	2-hourly		2-hourly
Data source	Corrected reflectance	Channel 02 (red)	Channel 13 (IR)	Pseudo-albedo
Number of scenes	94	234	562	425
Remarks				Classified after
24 h spin-up				

**Figure 3.** Overview of processing levels of the datasets including the variable names used in the respective datasets.

- *Level 2.* For the level 2 dataset, the data are merged by `classification_id`.

The `classification_id` is a unique identifier of a classification, where a classification refers here to the process of labeling a single image by a single user. The user might use several labels of the same or a different kind to completely classify a scene. This process eliminates overlaps of same-user classifications for each pattern and turns the data into masks rather than coordinates (see Fig. 3). In cases where same-user classifications of different patterns overlap, the overlapping region is counted towards all classified patterns. This case is not handled specifically, as it shows the uncertainty a user had to classify a specific region as one or the other pattern. Masks have the advantage of being more easily queried whether a specific location is influenced by a mesoscale pattern or not. This product is saved in the Zarr format.

- *Level 3.* To make working with the dataset easier, the percentage of agreement (p) among users on a specific pattern on each location is calculated and saved as level 3 data for each workflow. It is calculated as follows:

$$p_{\text{pattern}}(i, j) = \frac{\sum_0^U c(i, j)}{U}, \quad (3)$$

where U is the number of users that have seen the particular image; c is the classification mask from the level 2 data; and i, j is the geographic coordinates. Because the

labels of users that attributed several classes to a single pixel are not removed, $\sum p$ can be greater than 100 %. An additional *unclassified* category is introduced to capture the agreement on unclassified regions, which is implicitly visible in, e.g., Fig. 4. Figure 4 shows how participants agreed on the different patterns on 12 February depending on the workflow. This figure is continued in Appendix A, where this overview of daily averaged classifications is given for each day to give an impression of the dataset and in particular the presence and distribution of mesoscale patterns during the EUREC⁴A field campaign. This product is saved in the Zarr format.

3 Potential dataset use and reuse

The EUREC⁴A field campaign has been an international study with a wide range of research platforms and many minor objectives (Stevens et al., 2021). This dataset covers not only the core area of the experiment but also the wider area and time period. While the participating research airplanes and drones were mostly staying in the trade winds, some research vessels conducted measurements as far south as 6.5° N.

This dataset gives the opportunity to study all these measurements in the context of the mesoscale patterns observed in the downwind trades. Due to the high subjectivity of these mesoscale cloud pattern definitions, it is of particular importance to discuss results based on a common consensus to keep studies comparable. The C³ONTEXT dataset can serve

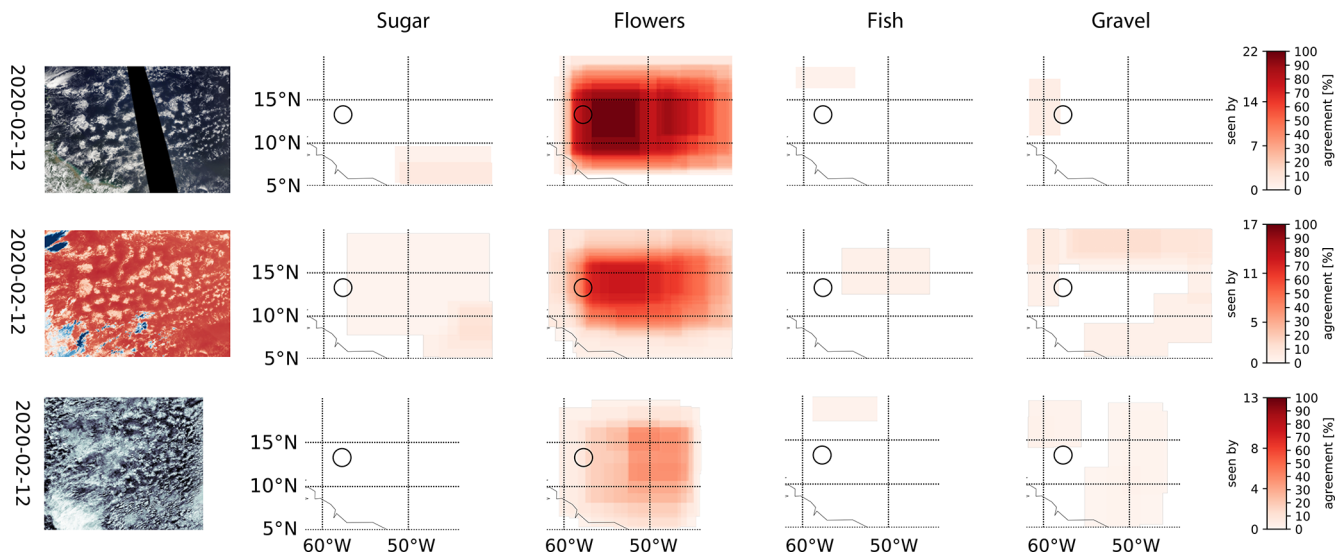


Figure 4. Manual-classification examples for the three workflows (top to bottom: visible, infrared and simulation). The labels for each pattern (from left to right: sugar, flowers, fish and gravel) are shown next to the labeled image. Coastline of South America is marked in black. The circle marks the EUREC⁴A circle, one focus area of the EUREC⁴A field campaign and the main flight pattern of the participating research aircraft HALO (High Altitude and Long Range Research Aircraft) (Konow et al., 2021). Coastlines are based on GSHHG (Global Self-consistent, Hierarchical, High-resolution Shorelines) shapefiles (Wessel and Smith, 1996). Please note that the date format in this figure is year-month-day.

as such a reference for the period of the EUREC⁴A field campaign.

Figure 5 shows the mesoscale context for three platforms participating in EUREC⁴A and representing different measurement strategies (see Stevens et al., 2021, for a complete list of platforms). Based on the classifications of the infrared workflow, the daily changes in the cloud patterns become apparent. The infrared workflow is preferred over the visible one because it covers both day and night and is therefore able to also capture the diurnal nature of the patterns (Vial et al., 2021). Before the intense observation period (IOP), 20 January to 20 February, the prevailing cloud pattern at the Barbados Cloud Observatory was gravel. With the start of the IOP, fish was detected most in the research area. After 24 January, patterns were much less widespread and well defined such that there was more disagreement on the patterns. This transition is independent of the location. Both the platforms in the north as well as R/V *Atalante*, which sailed further south in the Boulevard des Tourbillons (eddy boulevard), which is defined by Stevens et al. (2021) as the area of the coastline of Brazil where the North Brazil Current (NBC) rings occur, were embedded in a similar transition. The reduced frequency of classifications towards the end of the IOP around 15 February are caused by mid-level clouds obscuring the view of shallow convection.

In Appendix A the level 3 products are visualized for each studied day and can be used as a lookup table to quickly identify if a pattern has been identified at a specific time and place.

4 Comparison with other classifications

Several methods have been developed to describe the mesoscale structure of shallow convection (Wood and Hartmann, 2006; Rasp et al., 2020; Bony et al., 2020; Denby, 2020). Here we focus on the comparison of the manual classifications with two other methods that specifically aim to detect the four mesoscale patterns of the downwind trades as defined by Stevens et al. (2020) and shown in Fig. 1. Bony et al. (2020) combined a measure of organization (I_{org} , Tompkins and Semie, 2017) with the mean cluster size (S), while Rasp et al. (2020) developed a deep neural network to detect the patterns. Although Janssens et al. (2021) show that different combinations of metrics, like cloud fraction and fractal dimension, better describe the variance in a cloud field, the pair of I_{org} and mean cluster size has been widely used and is considered here for better comparison.

To assess the agreement between the different classification methods, we compare the method of Bony et al. (2020) and a deep neural network based on Rasp et al. (2020) that detects the patterns in geostationary infrared images of GOES-16 ABI (Schulz et al., 2021) instead of visible images taken on board the polar-orbiting satellites Terra and Aqua. It should be noted that this deep neural network has not been trained with the manual classifications presented here but with the manual classifications of Rasp et al. (2020) which cover older years and included different geographical regions. The network is identical to the one used in Schulz et al. (2021).

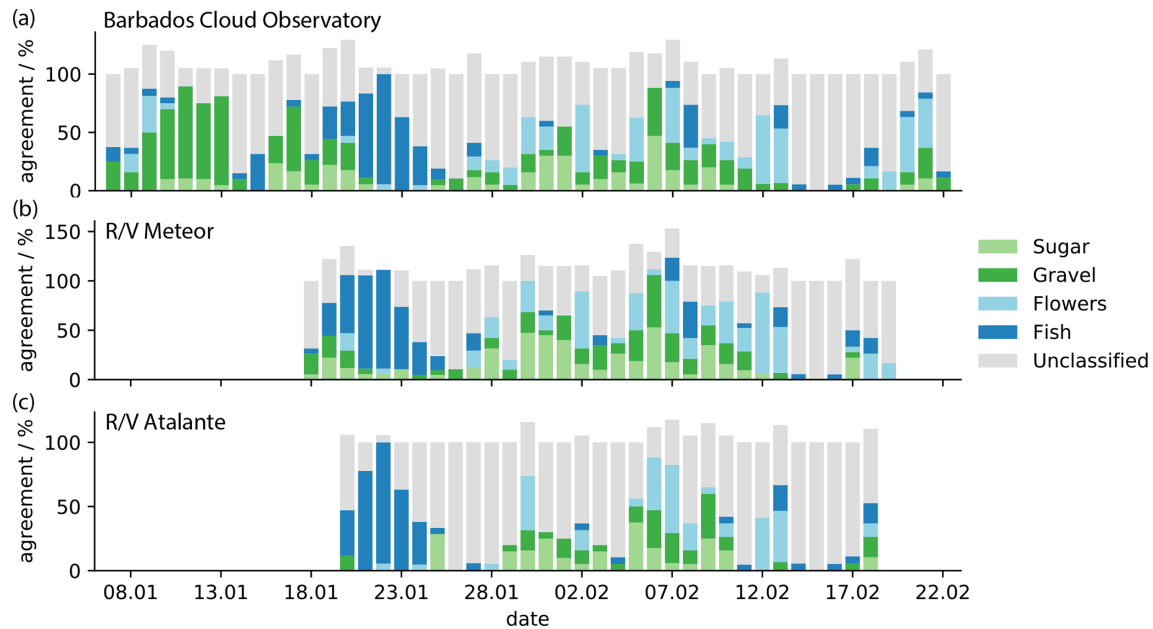


Figure 5. Exemplary use case of level 3 data: mesoscale setting of research platforms during EUREC⁴A based on the EUREC⁴A IR workflow (a–c: Barbados Cloud Observatory (BCO), R/V *Meteor* and R/V *Atalante*). Please note that the date format in this figure is day.month.

Because the I_{org}/S measure is sensitive to the domain size, we compute these metrics over a $10 \times 10^\circ$ sub-domain and consider only classifications within this domain for the comparison. Specifically, we focus on the region $10\text{--}20^\circ\text{N}$, $58\text{--}48^\circ\text{W}$. This domain size ensures that I_{org} describes the organization on the mesoscale and the cloud patterns we are interested in. The method has been successfully used in this domain in Bony et al. (2020) and applied accordingly. Brightness temperatures between 280 and 290 K are regarded as clouds. Days where the 25th percentile of brightness temperatures within any satellite image is lower than 285 K are discarded to avoid a bias by high clouds.

Figure 6 shows the comparison of the different methods. From the appearance of the patterns, we expect gravel and flowers to be rather regularly distributed and therefore to have a lower I_{org} compared to fish and sugar. It should be noted that I_{org} is calculated based on a threshold in brightness temperature, and therefore only the deeper clouds in the sugar field are considered leading to a higher I_{org} value than one would expect from an otherwise rather randomly distributed cloud field. The mean cluster size should be small for sugar and gravel and larger for flowers and fish.

Indeed, the pattern area fraction maximizes for each pattern in the respective quadrant of the I_{org}/S space independent of the classification method. Gravel classifications dominate the lower-left quadrant; sugar dominates the upper-left quadrant; and fish dominates the upper-right one. Flowers are harder to associate with a quadrant, as they are more centered. In general, the I_{org}/S distribution has a large range of

values for small mean cluster sizes and narrows with increasing mean cluster size.

This is also in alignment with Bony et al. (2020), where the lower-right quadrant includes not only flowers but also about 35 % of the fish cases (their Fig. 1c). Flowers' cloud entities are generally smaller than those of the fish pattern and therefore cannot separate very well from the other patterns.

Figure 7 reveals the time series of the area fraction covered by the mesoscale patterns within the region of $10\text{--}20^\circ\text{N}$, $58\text{--}48^\circ\text{W}$ and identified by the different classification approaches. For a better comparison with the EUREC⁴A VIS workflow, Fig. 7 is only based on daytime classifications (12:00–20:00 UTC).

To convert the agreement on patterns in the level 3 dataset into actual classifications, we applied a threshold of 0.1 to the percent agreement so that at least 10 % of participants who viewed a given scene must have agreed on a pattern. Agreement below this threshold is treated as an unclassified region. This threshold should be seen as a lower bound and is only used to reduce the noise of the classifications. For comparison, we also apply a stricter threshold of 0.5, which removes most of the overlap (Fig. 7b). The overall day-to-day changes remain robust. Figure 7 shows that in January–February 2020 all patterns were dominant at least once. It also shows that abrupt day-to-day changes of dominant patterns are rather rare, and a smooth transition from gravel to fish to sugar to flowers is observed.

Overall, the different classification methods agree well with each other, and no large discrepancies are found. This

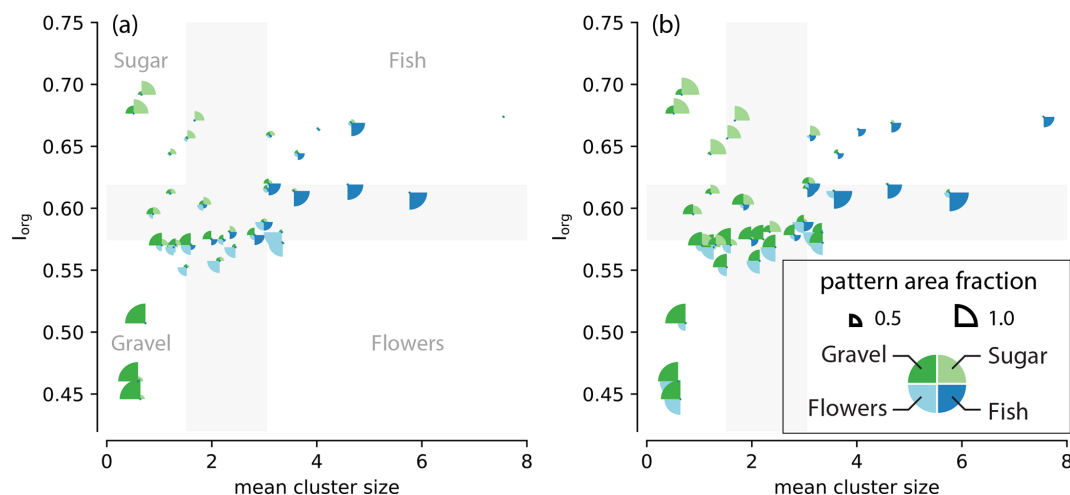


Figure 6. Comparison of the I_{org} versus mean cluster size (S) classification method and the (a) manually classified patterns and (b) the neural network classifications. For each I_{org}/S classification, the manually/automatically classified pattern area for each pattern is indicated as wedges of different sizes. Mean cluster size is given as a fraction of the domain size and multiplied by 10^4 to be consistent with Bony et al. (2020). Grey areas indicate the middle terciles of I_{org} and S and are the bounds of the four pattern quadrants. All classifications are based on the GOES-16 ABI infrared images and are daily averages.

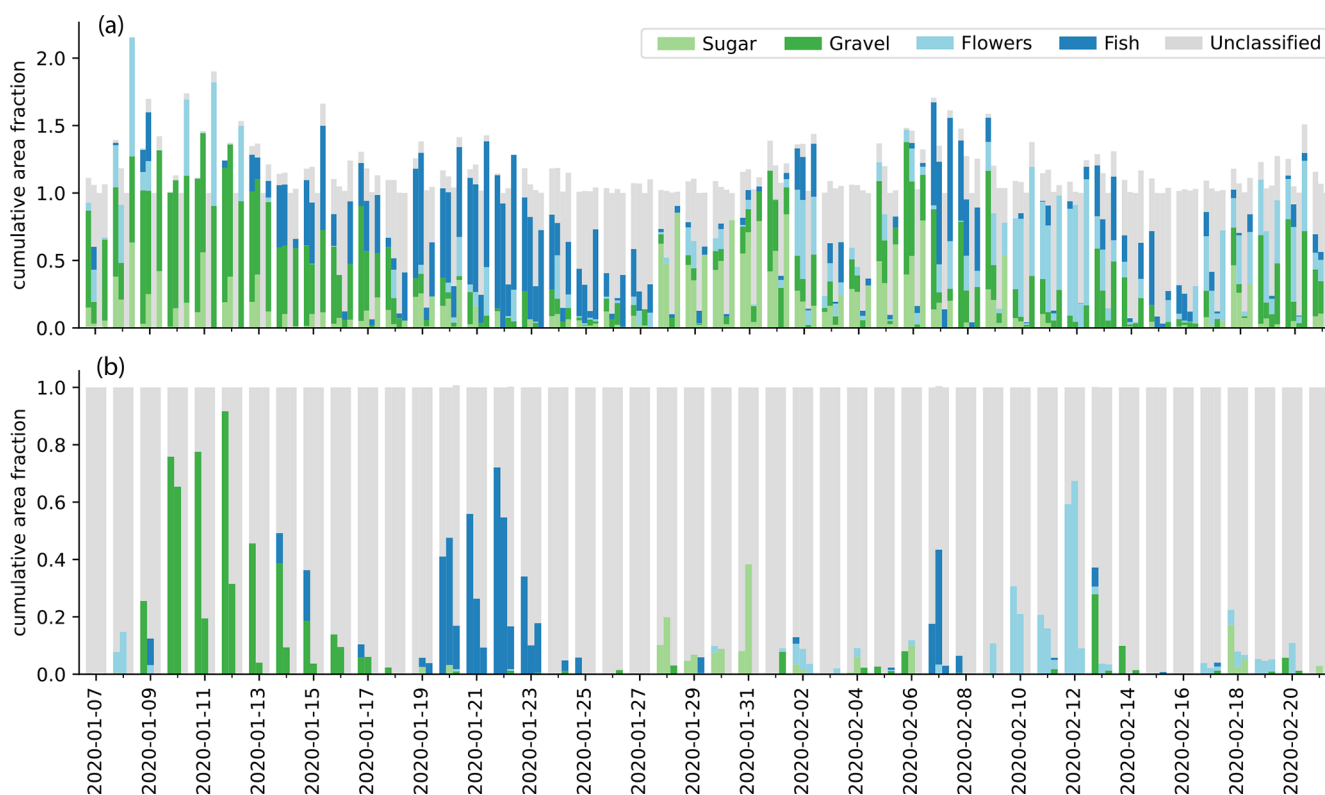


Figure 7. Time series of the area fraction covered by each pattern as identified in the workflows EUREC⁴A VIS (first bar), EUREC⁴A IR (second bar), EUREC⁴A ICON (third bar) and the deep neural network trained for the infrared classification of cloud patterns (fourth bar) in (a) within the area of 10–20°N, 58–48° W. Thresholds of 0.1 (a) and 0.5 (b) have been applied to the percentage of agreement of the manual classifications and visualize that the overlap of different categories (cumulative area fractions above 1) is eliminated in the latter. Please note that the date format in this figure is year-month-day.

confirms that these methods are valid for further analysis of mesoscale patterns. While the I_{org}/S metric is computationally cheap and can be easily applied to different regions, it is less suitable for short time periods because the terciles that attribute the I_{org}/S pairs to specific quadrants are not robust for a small sample size. Terciles from other studies can only be used if the resolution of the dataset is the same. For short time periods, like those of typical campaigns where people are interested in specific days or even sub-daily variations, manual classifications are advantageous, as they do not require a large sample size. The neural network approach presents a good opportunity to extend the classifications to different time periods and regions by using manual classifications as a training set. Here, the manual classifications served as an additional independent validation dataset and proved once more the capabilities of the neural network which has been trained on the dataset of Rasp et al. (2020).

5 Code and data availability

The C³ONTEXT dataset including raw data is openly available on the Zenodo database (European Organization For Nuclear Research and OpenAIRE, 2013; <https://doi.org/10.5281/zenodo.5979718>, Schulz, 2022a). The source code necessary to generate the dataset is available at <https://doi.org/10.5281/zenodo.5989155> (Schulz, 2022b) together with examples on how to process the data and retrieve the classifications for any platform as shown in, e.g., Fig. 5.

6 Conclusions

Mesoscale patterns of shallow convection are a main focus of the EUREC⁴A field campaign that took place in January and February 2020. To gain a better process understanding of shallow convection in the trades, the classifications of mesoscale patterns offer the opportunity to study the measurements in their mesoscale context and thereby split the observations into less complex pieces and disentangle otherwise superimposed processes. Here, we present C³ONTEXT, a dataset on the common consensus on the mesoscale patterns which occurred during the broader EUREC⁴A time period and emerges from the manual classifications done by members of the EUREC⁴A science team.

C³ONTEXT reveals that all mesoscale cloud patterns are observed during the studied period of January and February 2020. However, in the intense observation period of the EUREC⁴A field campaign, 20 January to 20 February, gravel was only sporadically identified and not prevalent in the study area. In contrast, a week before the intense observation period, gravel dominated in the research area. Instruments that were already running at this time, like those at the Barbados Cloud Observatory, were able to gain measurements under the mesoscale influence of gravel and complement the measurements from the IOP.

The difficulties of the participants to classify the patterns in the output of a storm-resolving simulation demands further investigation into how well simulations can capture the variability of mesoscale patterns of shallow convection in the trades.

A comparison of the manual-classification approach with other methods used in the literature to identify the four mesoscale patterns of shallow convection reveals a generally good agreement and confirms the validity of the different approaches. Nevertheless, the manual classifications are beneficial for limited temporal and spatial studies especially when the classifications are done by a group of several trained scientists. This presents a way to gain a consensus of subjectively defined cloud patterns without an additional layer of complexity from a neural network or any other algorithm.

In general, it has been shown that with little effort, classifications of the cloud field are possible and can be a huge benefit for the community, encouraging this approach for future studies.

Appendix A: Daily classification overview

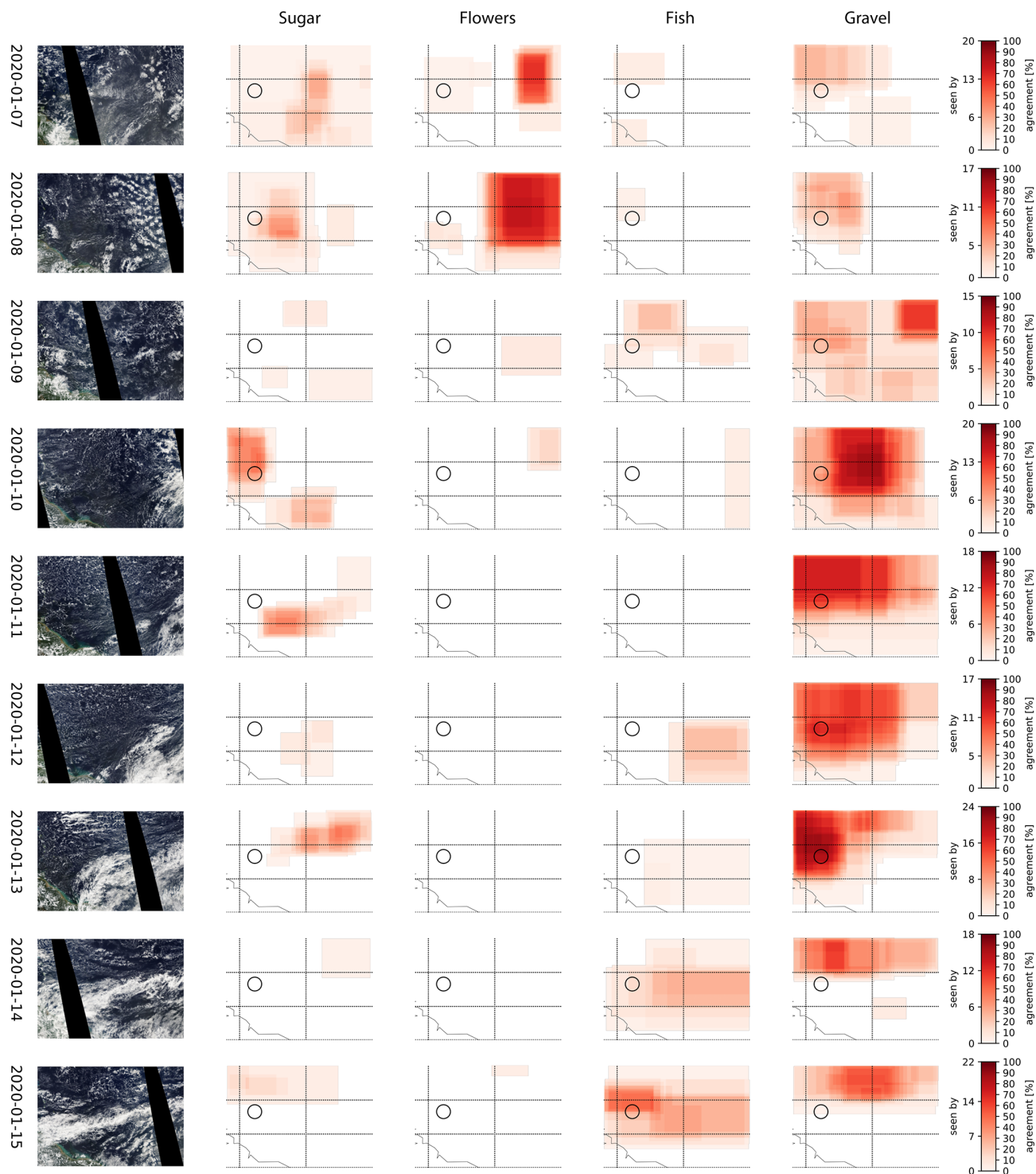


Figure A1.

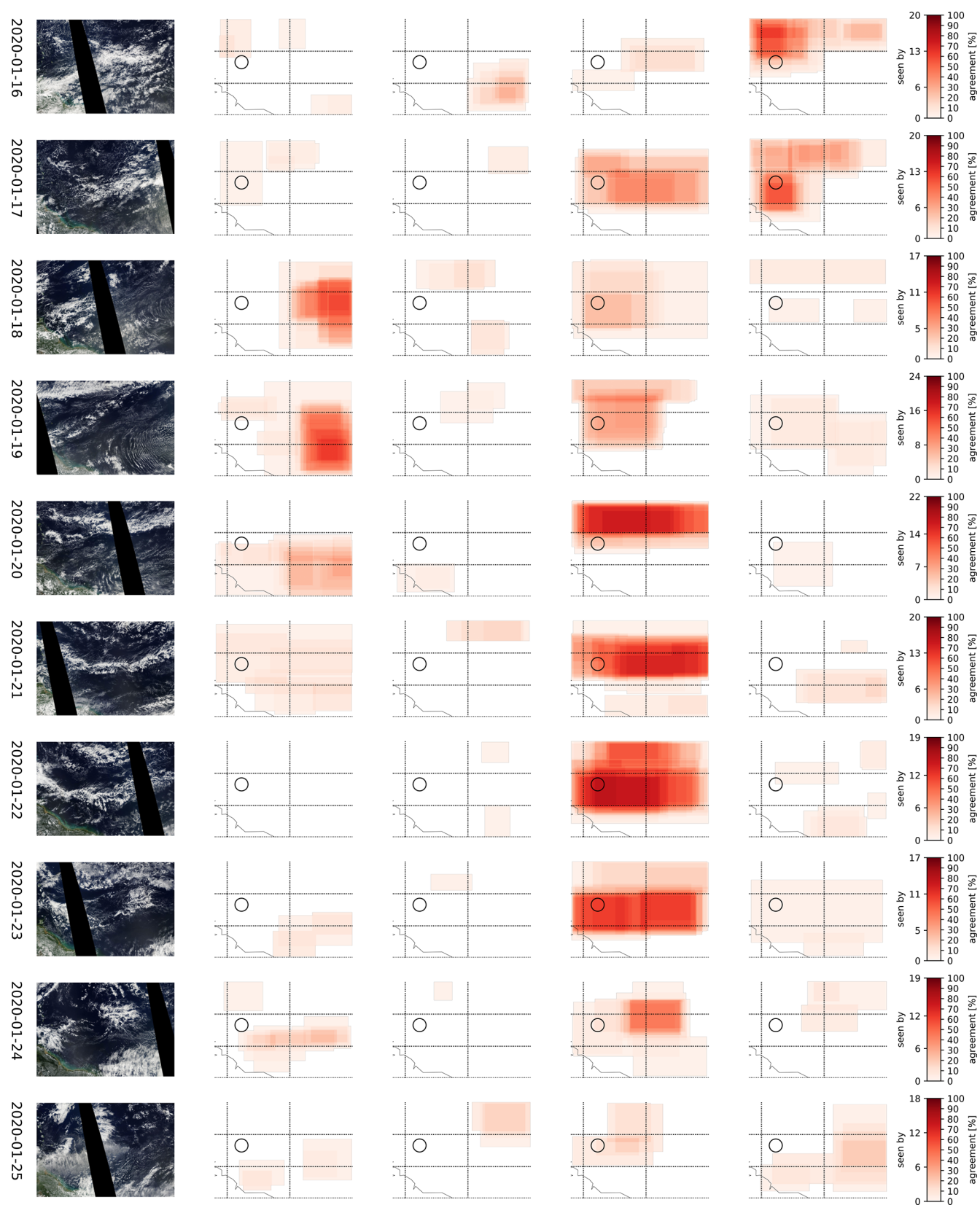


Figure A1.

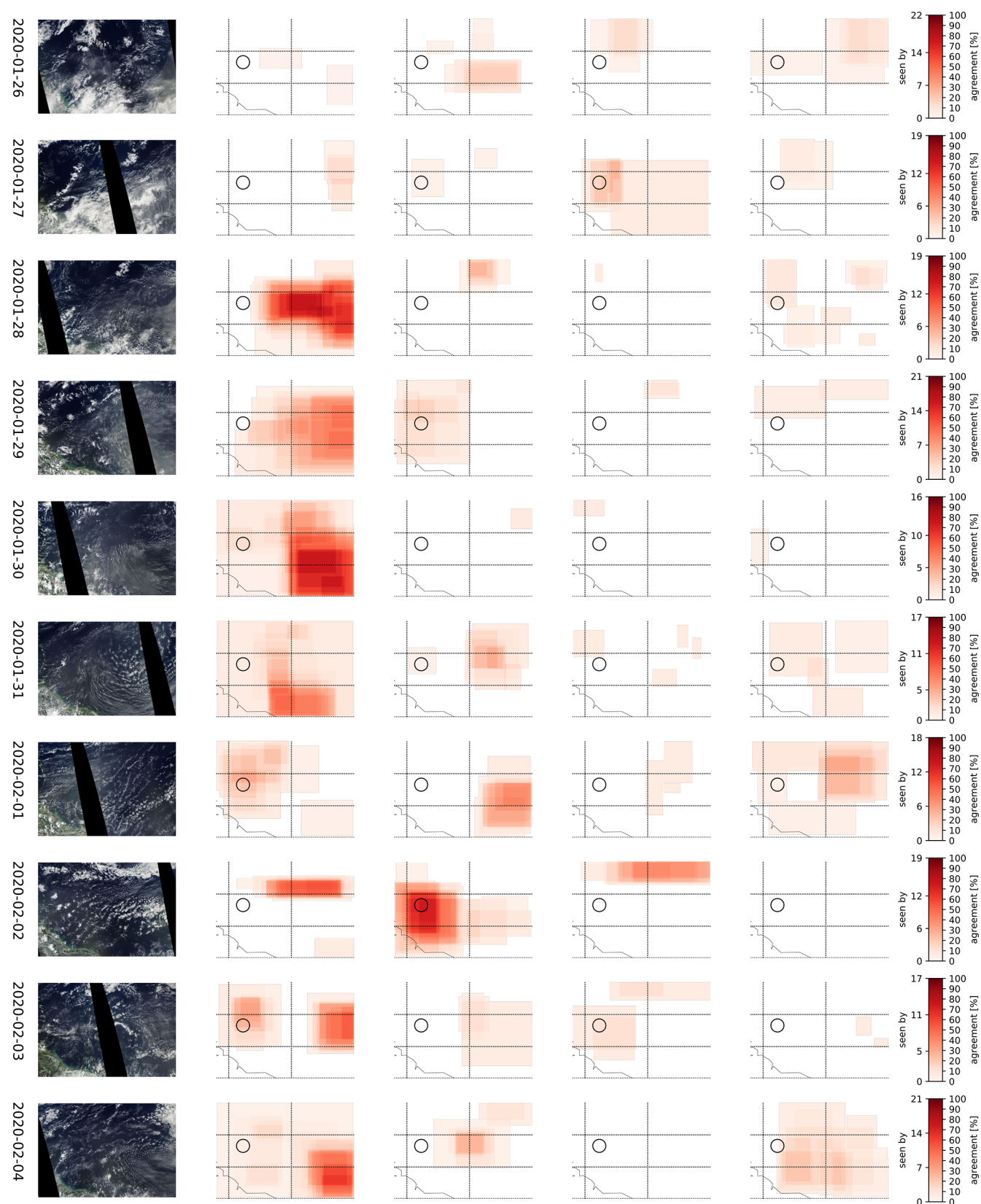


Figure A1.

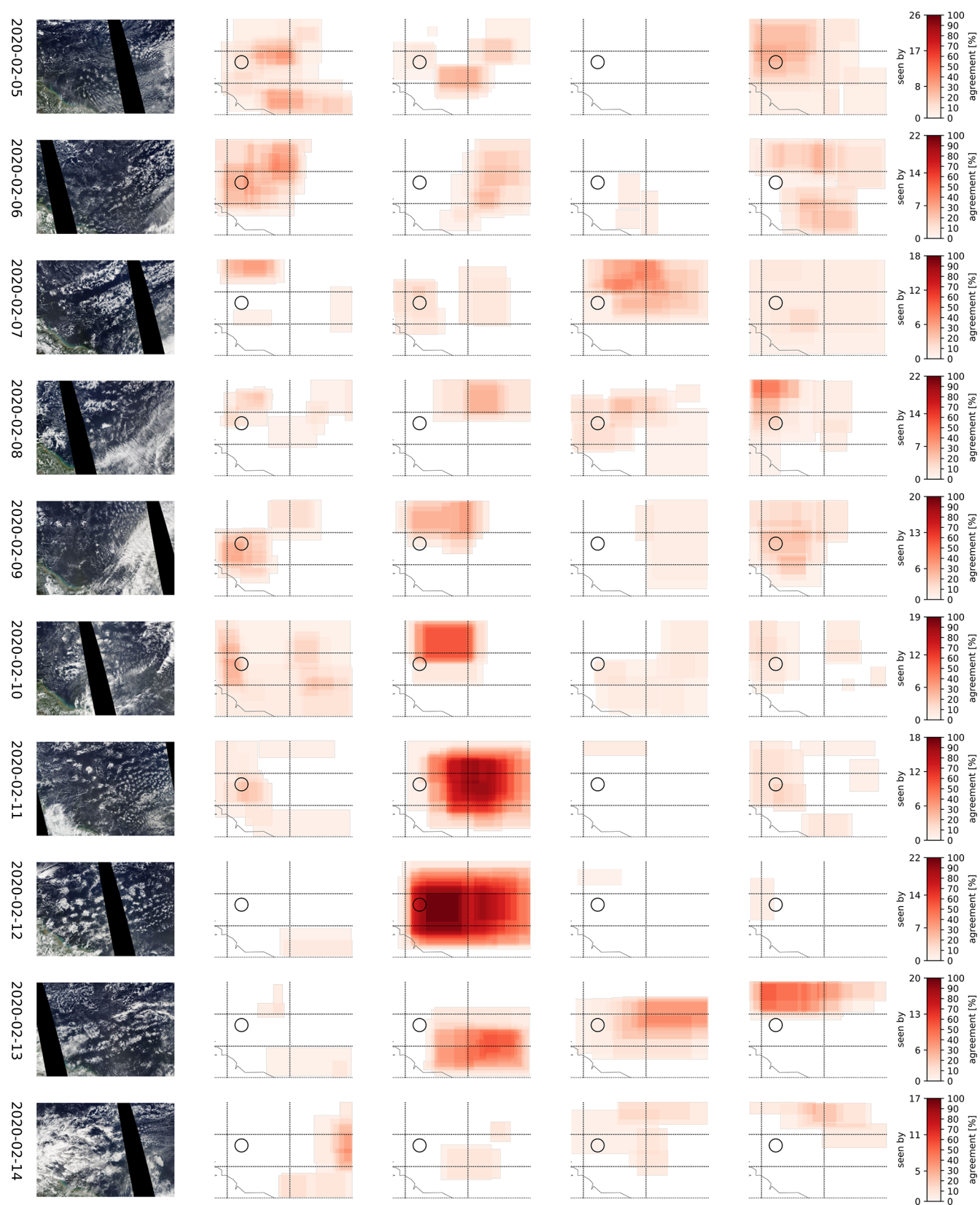


Figure A1.

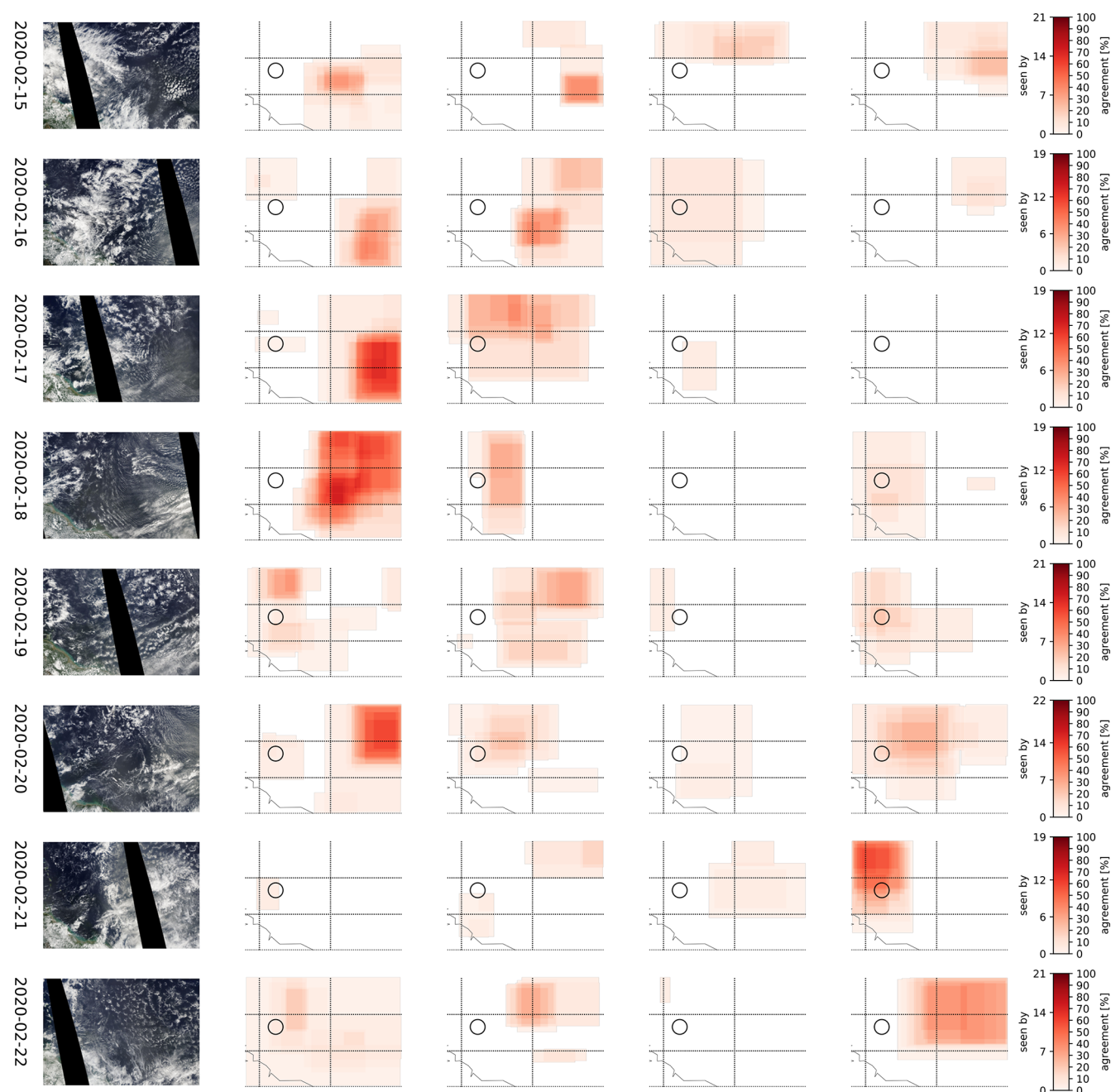


Figure A1. Heatmaps of manual classifications based on MODIS (Aqua and Terra) visible imagery. Left to right: visible imagery during an Aqua overpass and user agreement on sugar, flowers, fish and gravel. The circle marks one focus area of the EUREC⁴A field campaign and the main flight pattern of the participating research aircraft HALO (Konow et al., 2021). Coastlines are based on GSHHG shapefiles (Wessel and Smith, 1996). Please note that the date format in this figure is year-month-day.

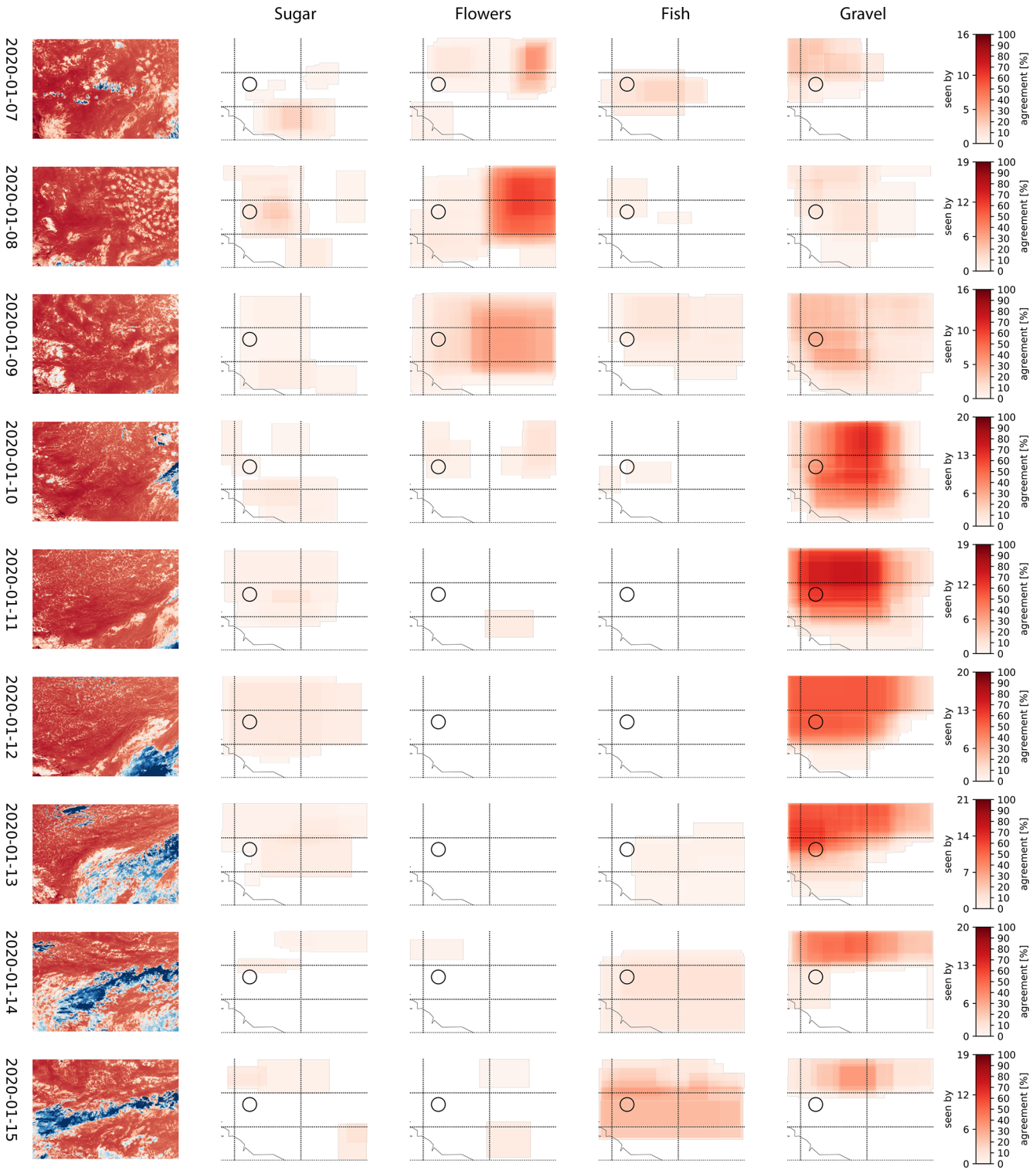


Figure A2.

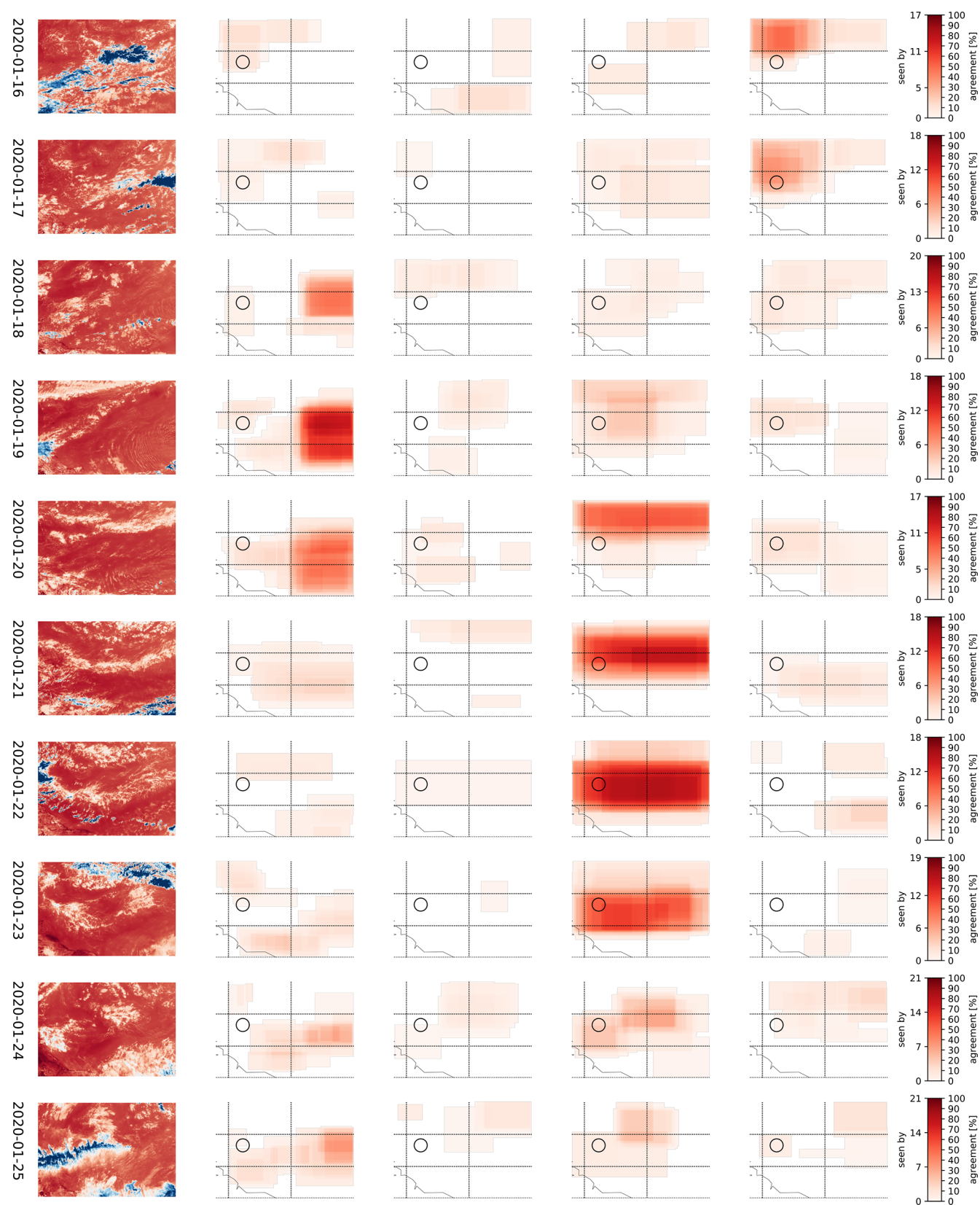


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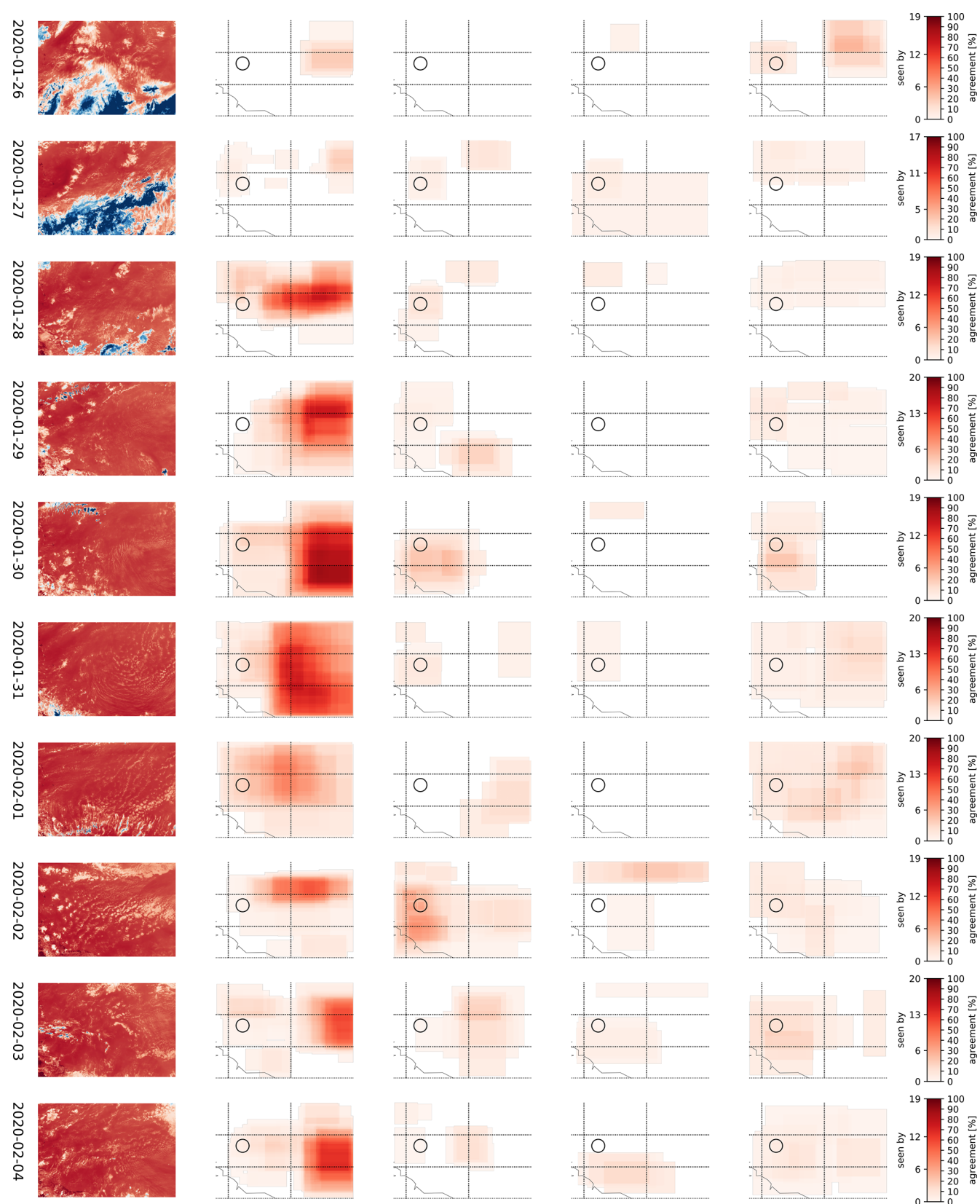


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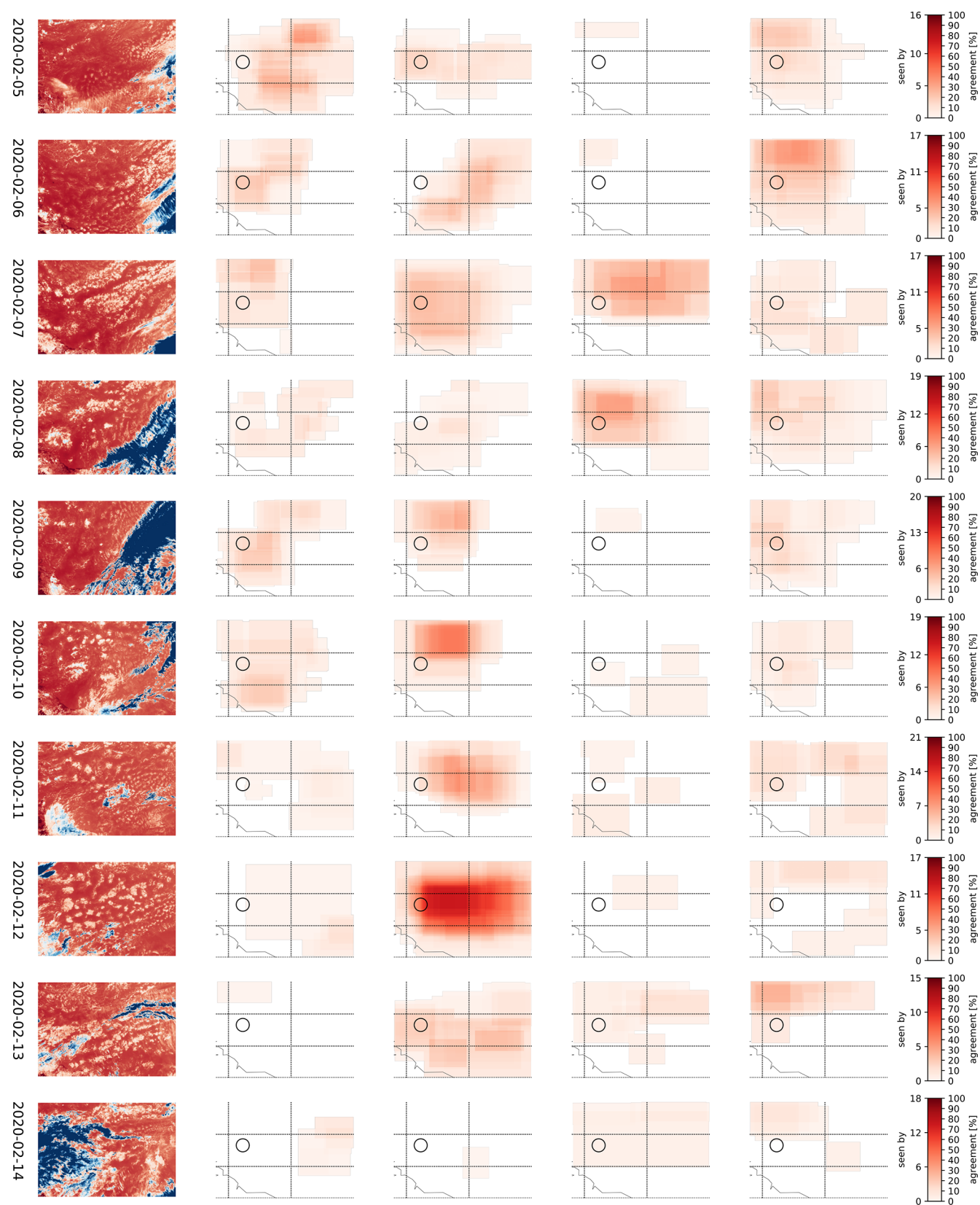


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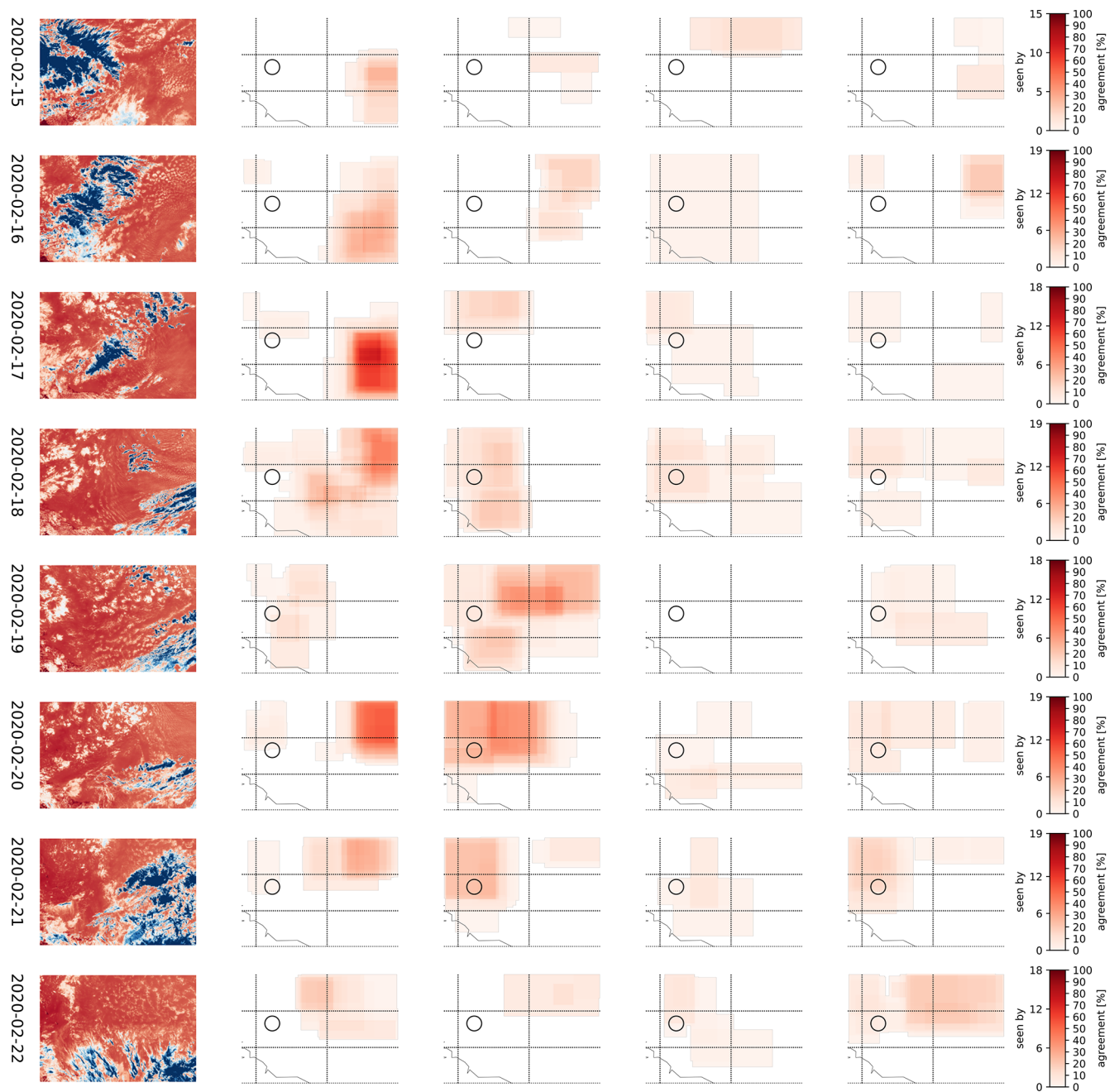


Figure A2. As Fig. A1 but for the infrared workflow. Images show the cloud field at 16:00 (except 11 February 2020 at 17:00). Please note that the date format in this figure is year-month-day.

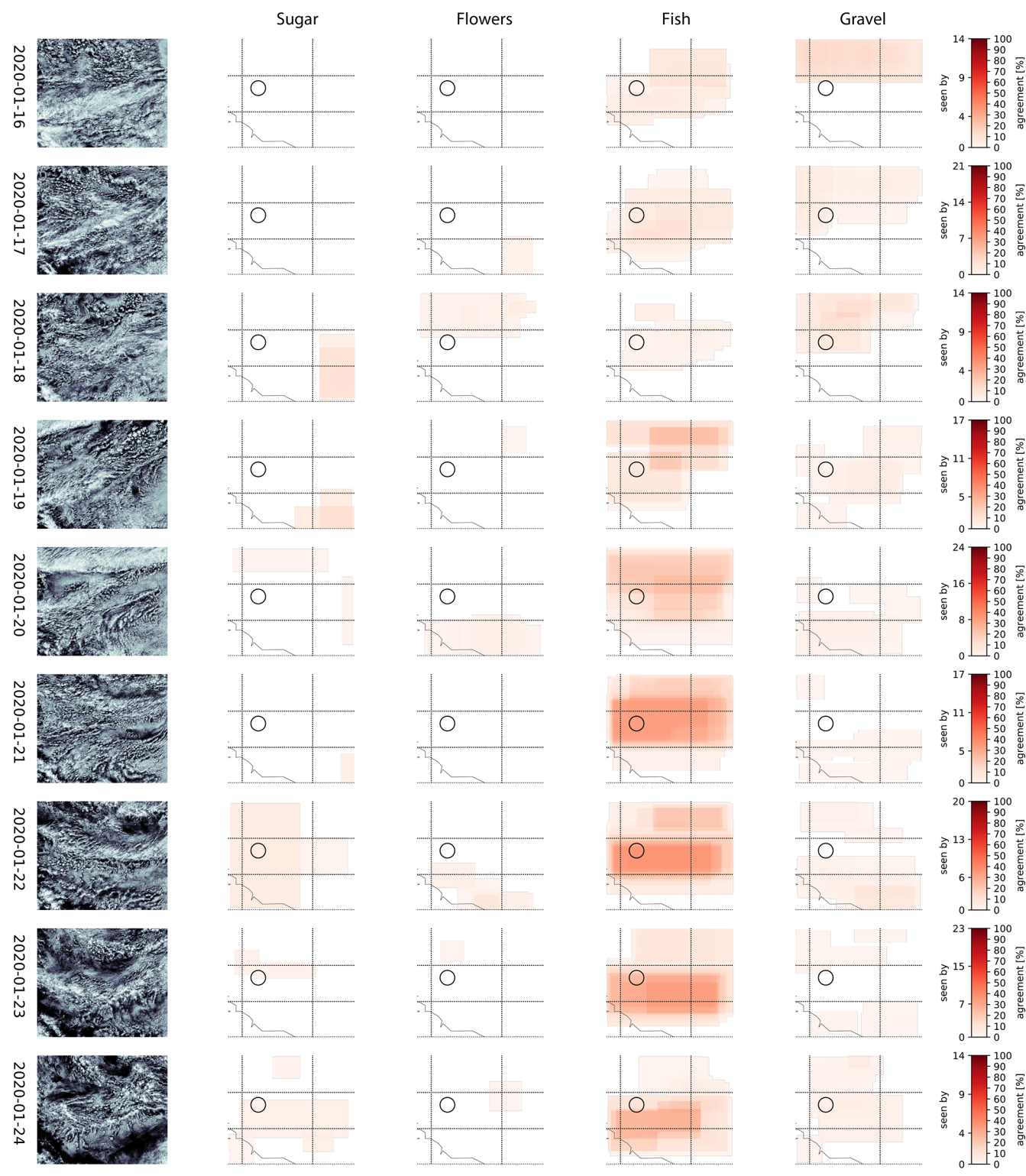


Figure A3.

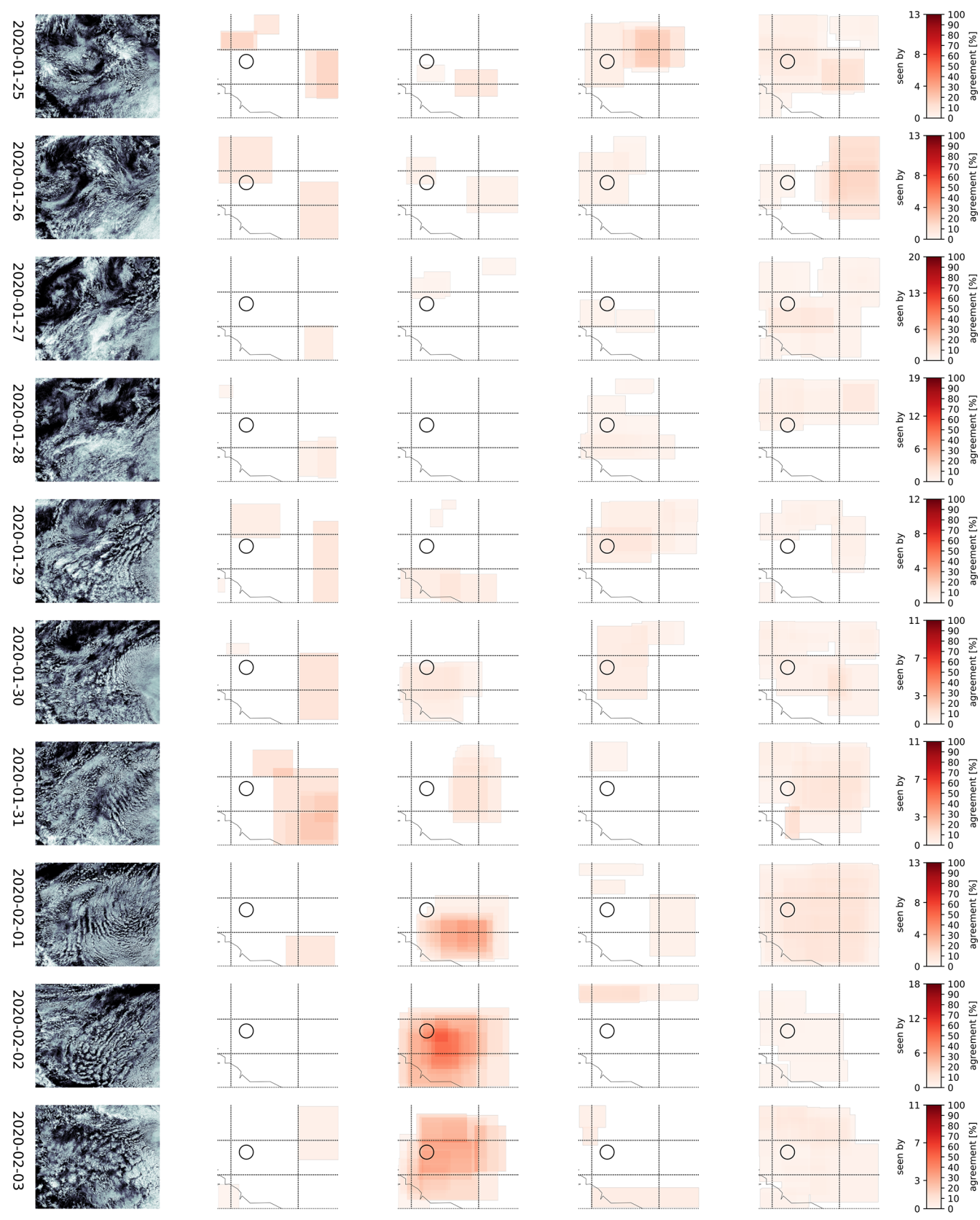


Figure A3.

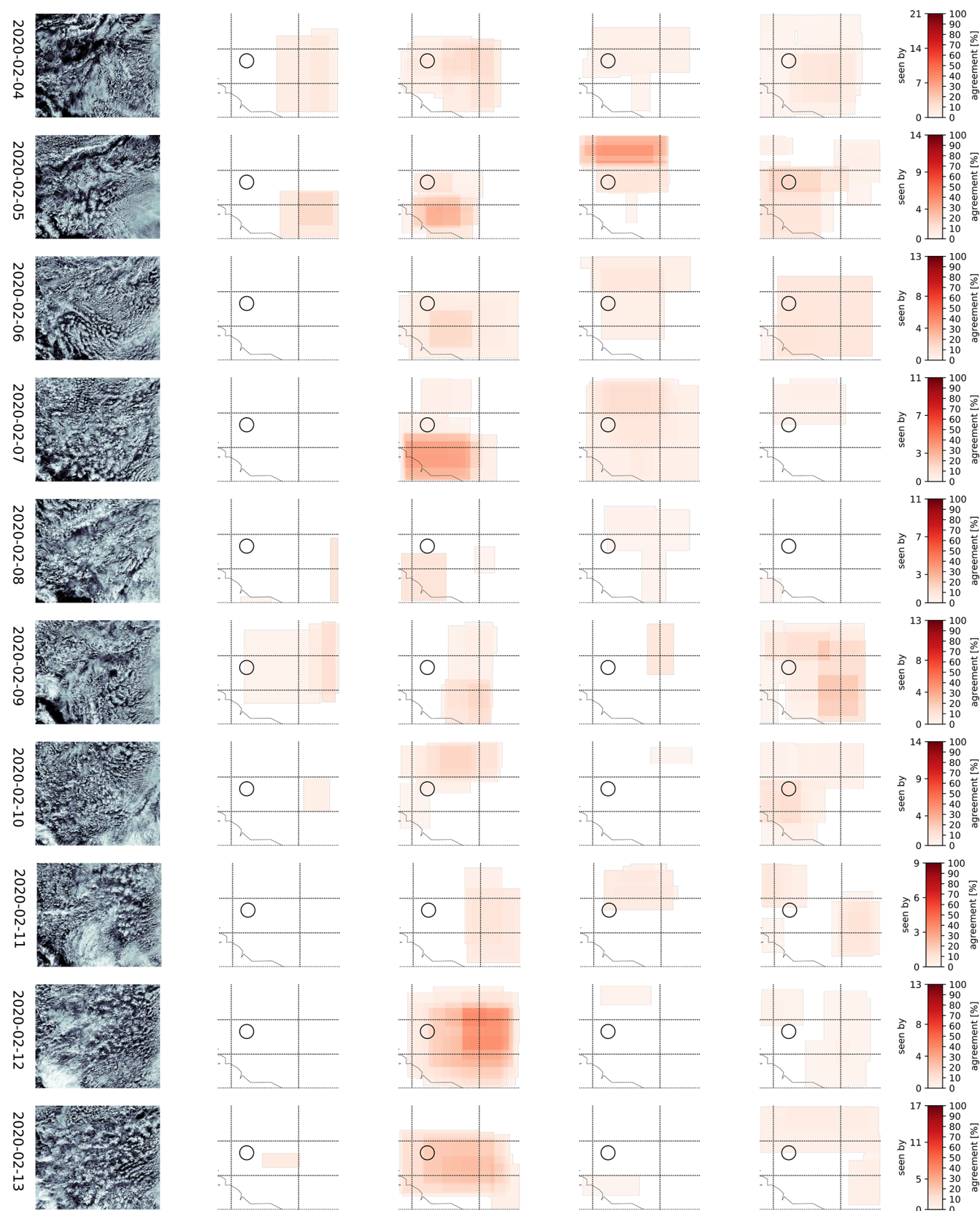


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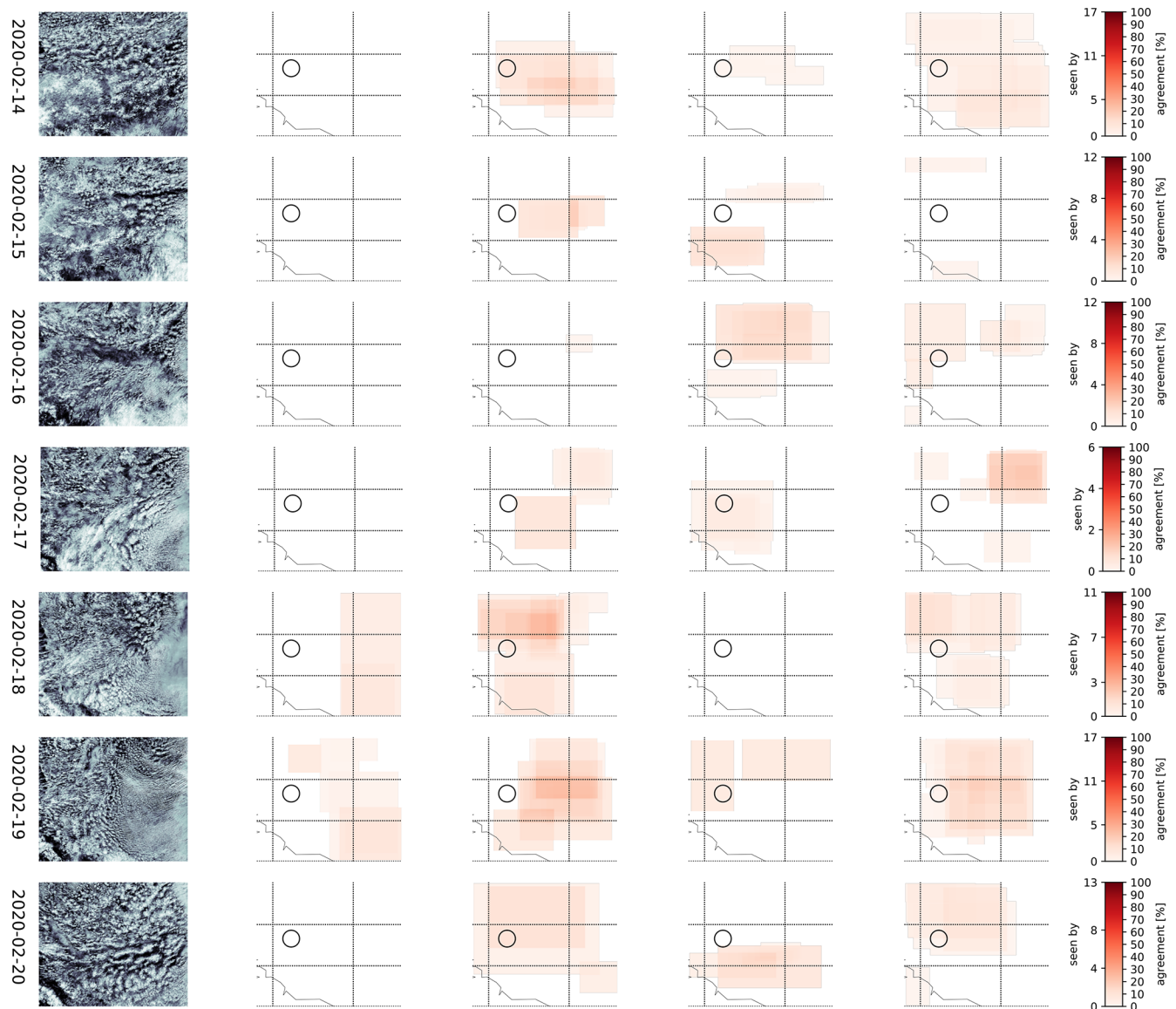


Figure A3. As Fig. A1 but for the ICON albedo workflow. Images show the cloud field at midnight. Please note that the date format in this figure is year-month-day.

Competing interests. The contact author has declared that there are no competing interests.

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