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Summertime Convective Initiation Nowcasting over Southeastern China

Based on Advanced Himawari Imager Observations

Running title: CI Nowcasting using AHI

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Abstract

Convective initiation (CI) nowcasting often has a low probability of detection (POD) and a high false-alarm ratio (FAR) at sub-tropical regions where the warm-rain processes often occur. Using the high spatial- and temporal-resolution and multi-spectral data from the Advanced Himawari Imager (AHI) on board Japanese new-generation geostationary satellite Himawari-8, a stand-alone CI nowcasting algorithm is developed in this study. The AHI-based CI algorithm utilizes the reflectance observations from channels 1 (0.47 μm) and 7 (3.9 μm), brightness temperature observations from infrared window channel 13 (10.4 μm), the dual-spectral differences between channels 10 (7.3 μm) and 13, 13 and 15 (12.4 μm), as well as a tri-spectral combination of channels 11, 15 and 13, as CI predictors without relying on any dynamic ancillary data (e.g., cloud type and atmospheric motion vector products). The proposed AHI-based algorithm is applied to CI cases over Fujian province in the Southeastern China. When validated by S-band radar observations, the CI algorithm produced a POD as high as 93.33%, and a FAR as low as 33.33% for a CI case day that occurred on 1 August 2015 over Northern Fujian. For over 216 CI events that occurred in a three-month period from July to September 2015, the CI nowcasting lead time has a mean value of ~64 minutes, with a longest lead time over 120 minutes. It is suggested that false-alarm nowcasts that occur in the presence of capping inversion require further investigation and algorithm enhancements.

Keyword: AHI; Convective initiation; Nowcasting
1. Introduction

Thunderstorms are often associated with meteorological hazards such as heavy rain, large hail, strong winds, tornadoes and lightning (Wang et al. 2004; Wagner et al. 2008), which may cause huge socioeconomic damage. To reduce the economic loss and avoid personnel casualty, it is important to monitor and forecast occurrences, development, and movement of thunderstorms in a timely manner with great accuracy (Merk and Zinner, 2013; Lee et al., 2017).

Weather radar is a useful tool for identifying and tracking mature thunderstorms. Radar measurements can be used to retrieve three-dimension wind fields and hydrometeor distributions within a thunderstorm which improve the analysis and prediction of the thunderstorm’s structure and evolution. Many radar-based algorithms were developed, such as the Thunderstorm Identification, Tracking, Analysis, and Nowcasting (TITAN) algorithm (Dixon and Wiener, 1993), the Storm Cell Identification and Tracking (SCIT) algorithm (Johnson et al., 1998), and the Radar Tracking and Monitoring (RadTRAM) algorithm (Kober and Taffener, 2009). However, there exist limitations of weather radars. Firstly, due to the radar placement, beam blockage, Earth curvature and atmospheric refraction, there are data gaps among the current radar networks or below the lowest radar elevation, especially in the mountainous areas. Moreover, operational radars are mostly sensitive to relatively large objects (e.g., raindrops and hail), and are thus not adequate in capturing vertical cloud growth prior to an occurrence of a precipitating thunderstorm when precipitation echoes are not yet observable.

Convective initiation (CI) is defined as the first occurrence of rainfall with reflectivity
intensity being greater than 35 dBZ as measured by ground-based weather radar (Roberts and Rutledge, 2003). According to a relationship between reflectivity (Z) and rainfall (R), to be called Z-R relationship for brevity, a rainfall rate with reflectivity intensity of 35 dBZ corresponds to a moderate rainfall at 5.38 mm h\(^{-1}\) for summer deep convection (Woodley and Herndon, 1970). Therefore, CI refers to an interval when an existing shallow cumulus cloud evolves into a cumulonimbus cloud or precipitating thunderstorm. CI occurs preferably in an unstable, moist environment. Although a stability index, such as convective available potential energy (CAPE), could be used to identify regions where the CI is likely to occur (Johns and Doswell, 1992; Pryor, 2015), it is difficult to predict the exact CI location and time due to insufficient spatial and temporal resolution of surface-station observations and numerical weather prediction models.

The geostationary operational environmental satellite (GOES) imagers make measurements at infrared and visible spectral regions with high spatial resolution (1-4 km) and rapid refresh rate (~15 min), providing an optimal means of monitoring and forecasting CI occurrences (Walker et al., 2012). The visible and infrared radiance measurements from GOES imagers are extremely sensitive to cloud droplets within a cumulus cloud as soon as a cloud expands to the subpixel scale (~1 km) of GOES imagers. The cloud-top glaciation and updraft strength inferred from the multispectral infrared satellite images can be used for diagnosing immature cumulus clouds that will continually grow to form precipitating thunderstorms (Morel and Senesi, 2002; Sobajima, 2012). Roberts and Rutledge (2003) examined several thunderstorm cases over eastern Colorado. By monitoring the time trends of cloud-top phase and temperature with the GOES-8 imager, a forecast lead time of longer
than 30 min can be achieved before a CI is detected by ground-based radars. Roberts and Rutledge (2003) provided a framework for the development of various satellite-based CI nowcasting algorithms, such as the pixel-based University of Wisconsin CI (UWCI) nowcasting algorithm (Sieglaflf et al., 2011) and the cloud-object-based Satellite Convection Analysis and Tracking (SATCAST) algorithm (Mecikalski and Bedka, 2006; Walker et al., 2012). In the UWCI algorithm, the infrared brightness temperature (BT) from cloudy pixels within a 7x7 pixel box (~784 km² at sub-satellite point) are firstly averaged to derive a box-averaged BT field. Secondly, differences of the box-averaged BT field between two successive images are used to retrieve the cloud-top cooling (CTC) rate. Thirdly, a cloud-type dependent filtering is carried out to eliminate pixels of false cooling due to cloud motion or cirrus contamination (Pavolonis, 2010). Finally, pixels with a filtered CTC rate being less than -4.0 K (15 min)⁻¹ are assigned a CI nowcast. Different from the UWCI algorithm, the SATCAST algorithm treats each cumulus cloud object as a single entity. The SATCAST algorithm consists of three main components, namely the cumulus cloud mask generation, cloud-object tracking, and CI forecast determination. To track a cloud object, the temporal overlap approach proposed by Zinner et al. (2008) is used along with the atmospheric motion vector product (Bedka et al., 2009). In the CI determination, a series of spectral and temporal difference tests relevant to the assessment of CI potential are performed to determine the coldest updraft regions within cloud objects. The SATCAST algorithm achieves a probability of detection (POD) of 85% and a false-alarm ratio (FAR) of 55% over central U.S./Great Plains domain. However, as mentioned in Walker et al. (2012), PODs are lower for CI events occurring in the sub-tropical environment where higher moisture leads warm-rain processes.
to form before a cloud-top glaciation.

The Advanced Himawari Imager (AHI) on board Himawari-8, which is positioned above the equator at 140.7°E, is the first of new-generation geostationary meteorological satellites operated by Japan Meteorological Agency. AHI/Himawari-8 scans the full disk of the Eastern Hemisphere every 10 minutes with a horizontal resolution of 0.5-2 km at sub-satellite point (Bessho et al., 2016). This study presents a new CI nowcasting algorithm applicable to AHI observations. Similar to the SATCAST algorithm, the proposed CI algorithm also consists of three parts: cumulus cloud mask generation, cloud-object tracking, and CI forecast determination. The objectives of this research are (1) to adapt the SATCAST algorithm to the sub-tropical regions; (2) to make the SATCAST independent of the dynamic ancillary data, such as cloud types and atmospheric motion vector products, in order to generate CI forecasts as quickly as possible; and (3) to examine how reasonably the newly-added channel combinations describe cloud-top properties of developing cumuli.

This paper is organized as follows: Sections 2 provides a brief description of the data employed in this study. Section 3 details the technique differences between this algorithm and the SATCAST algorithm. The CI results obtained by the proposed CI algorithm are verified with ground-based radar observations in the subtropical region in section 4. Summary and conclusions are given in section 5.

2. Data Description

Fujian is a province located near the southeast coast of China over the area (24-28°N, 116-120°E). It is characterized by a temperate, humid, and subtropical climate. The mountains and hills make up the vast majority of Fujian's territory (see Fig. 1). Such an
atmospheric condition and orographic forcing increase the probability of CI occurrence over Fujian. Therefore, Fujian is chosen as the domain of interest in this study.

2.1 Radar Images

Measurements of radar reflectivity used in this study come from nine S-band China’s New Generation Doppler Weather Radars (CINRAD) placed at Shangrao, Wenzhou, Jianyang, Sanming, Fuzhou, Longyan, Quanzhou, Xiamen and Meizhou, respectively (Fig. 1). Each S-band CINRAD radar produces a volume scan approximately every six minutes. In this paper, CI is defined as the first occurrence of $\geq 35$ dBZ echo on the composite reflectivity images. The composite reflectivity is the maximum reflectivity from all elevation angles. Based on this definition, 27 CI days with a total of 157 daytime and 59 nighttime CI events are identified during the three-month period from July to September 2015 (Table 1). The day and night discrimination is based on whether the solar zenith angle is less than 60° or not. Among these 157 daytime CI events, only 35 did not undergo significant splitting or merging, and they are used in the selection of CI predictors. The CI events occurring during the winter season, although existing, are quite rare and not investigated in this study.

2.2 AHI data

The Japanese AHI/Himawari-8 has three visible channels, three near-infrared channels and 10 infrared channels (Table 2). Compared to its predecessor, the Multi-functional Transport Satellite (MTSAT) imagers with one visible and four infrared channels, the AHI provides more channels to better characterize the surface and cloud top features, as well as the vertical profiling of the atmosphere. The sub-satellite resolutions of AHI are 0.5 km for channel 3, 1 km for channels 1, 2 and 4, and 2 km for the other 12 channels. In this study, the
full-disk images of all 16 AHI channels are cropped to a proper size and then remapped into a 0.5-km Lambert Conformal projection, true at 30°N and 60°N. By doing so, the low-resolution infrared channels can be directly combined with the visible channels, while the fine detail provided by high-resolution visible channels can be preserved. The AHI cloud type and atmospheric motion vector products are not employed in this study.

2.3 Interest Fields Selection

The CI predictors are selected from 12 channels or channel combinations (hereafter, interest fields) defined by AHI visible and infrared channels. Although in principle the 16 AHI channels can be used to build a set of more than 100 interest fields by dual- or triple-channel combinations, many have redundancy in physical attributions. For example, measurements from channels 1-4 are sensitive to the cloud optical thickness and thus have a correlation greater than 0.90 between any two of them. It is not necessary to use all the four channels for constructing CI predictors reflecting cloud optical thickness. With regard to the contrast between the surface and cloud top, channel 1 reflectance ($\rho_{0.47}$) is the most significant among channels 1-4 (Zhuge et al. 2017). Therefore, a subset of 12 candidate interest fields are selected for describing the atmospheric states and cloud-top properties (Table 3). It is reminded that all the visible and near-infrared fields have been normalized by the solar zenith angle (Zhuge et al. 2012). The physical meanings for the 12 candidate interest fields are briefly described as follows:

1) AHI Channels 8-10 are water-vapor-sensitive. The peak weighting function levels for channels 8-10 with respect to US 1976 standard atmosphere are ~375, ~450, and ~600 hPa, respectively (Zou et al., 2016). For clear-sky and low-cloud scenes, the
BTs of channels 8 (i.e., $T_{b,6.2}$), 9 (i.e., $T_{b,6.9}$), and 10 (i.e., $T_{b,7.3}$) reflect the water vapor contents within upper, middle, and lower tropospheric layers, respectively. For middle and high clouds, $T_{b,6.2}$, $T_{b,6.9}$, and $T_{b,7.3}$ remain unchanged unless the cloud top reaches their peak weighting function levels. The BT difference (BTD) between channels 9 and 10 (i.e., $T_{b,6.9}-T_{b,7.3}$) can be utilized for estimating whether a cloud has grown to a given altitude (Matthee and Mecikalski, 2013). $T_{b,6.9}-T_{b,7.3}$ is mostly negative (~ -15 K) when the moist layer is at ~500 hPa and meanwhile the cloud top is lower than ~600 hPa. An elevated cloud top or moist layer would increase the value of $T_{b,6.9}-T_{b,7.3}$.

2) The BT of channel 13 (i.e., $T_{b,10.4}$) and the BTD between channels 10 and 13 (i.e., $T_{b,7.3}-T_{b,10.4}$) are indicators of cloud-top height. As the cloud top is elevated, the value of $T_{b,10.4}$ decreases, while $T_{b,7.3}-T_{b,10.4}$ increases. $T_{b,7.3}-T_{b,10.4}$ will turn from negative to zero values if the cloud top is elevated to upper troposphere (~300 hPa). According to Walker et al. (2012), $T_{b,7.3}-T_{b,10.4}$ is also an indicator of mid-level capping inversion.

3) Besides $\rho_{0.47}$, the BTDs between channels 15 and 13 (i.e., $T_{b,12.4}-T_{b,10.4}$) can also describe the cloud optical thickness. The values of $T_{b,12.4}-T_{b,10.4}$ are significantly negative for a thin cloud and increase as the cloud deepens (Strabala et al., 1994). The difference between $T_{b,12.4}$ and $T_{b,10.4}$ is also determined by cloud-top effective radius.

4) The tri-channel difference of channels 11, 15 and 13 (i.e., $T_{b,8.6}+T_{b,12.4}-2T_{b,10.4}$) is utilized to infer the cloud-top phase (Baum et al., 2000). The physical consideration for cloud-top phase discrimination is based on the difference between ice and liquid
water particle absorption spectra within the wavelength range 8-13 μm. The ice
absorption coefficient increases faster between 8 and 11 μm than between 11 and 12
μm, while the opposite is true for liquid water. As a result, ice (water) clouds tend to
have larger (smaller) values of $T_{b,8.6}-T_{b,10.4}$ than those of $T_{b,10.4}-T_{b,12.4}$. The tri-channel
difference is positive for ice-phase cloud top, while negative for water-phase cloud
top. An increasing tri-channel difference means the cloud-top is gradually glaciated.
Note that the tri-channel difference algorithm was found to be less accurate in regions
where more than one cloud phase types occur, and needs to be updated (Baum et al.,
2012).

5) The reflectance values of channels 5 (i.e., $\rho_{1.6}$), 6 (i.e., $\rho_{2.3}$), and 7 (i.e., $\rho_{3.9}$) are
correlated with the hydrometeor particle sizes (effective radius) in both liquid and ice
phases of water vapor (Nakajima and King, 1990). However, due to the differences of
the indices of refraction at different wavelengths (Mecikalski et al., 2010),
correlations between any two of $\rho_{1.6}$, $\rho_{2.3}$, and $\rho_{3.9}$ are lower than 0.8. Therefore, these
three interest fields are all retained for the further assessment. $\rho_{3.9}$ is derived from the
measurements of channels 7, 13 and 16 to remove the portion of thermal emission
(Setvak and Doswell 1991; Lensky and Rosenfeld 2008).

3. Algorithm Description

The CI nowcasting algorithm focuses mainly on immature cumulus clouds before they
grow into cumulonimbus clouds or precipitating thunderstorms. After a CI occurrence, a
thunderstorm would be formed and the CI detection is “turned off” by the CI nowcasting
algorithm. Therefore, a CI nowcasting algorithm should avoid contaminations from clear sky,
cirrus and mature cumulonimbus. The algorithm proposed in this study utilized in part the framework of the SATCAST algorithm (Walker et al., 2012) and includes three components: cumulus cloud mask, cumulus-object tracking, and CI forecast determination. Limited by the low spectral and temporal resolutions of the old-generation GOES imagers, the original SATCAST algorithm adopted several computationally expensive procedures and added dynamic ancillary data to obtain a good accuracy. The newly added channels and improved spatial and temporal resolutions of AHI/Himawari-8 allows a development of a computationally more efficient CI nowcasting algorithm without invoking any dynamic ancillary data. The AHI channels employed in the new CI nowcasting algorithm are provided in Table 2. More details about the three components of the CI algorithm are described below.

3.1 Cumulus Cloud Mask

The cumulus cloud mask component includes the following three steps (Fig. 2): 1) thick-cloud pixel identification from AHI multispectral images; 2) cloud object identification for grouping neighboring cloud pixels into an individual cloud object; and 3) a 10.4-μm infrared threshold for separating cumulus objects from thunderstorm objects. The first step separates thick-cloud pixels from clear-sky and thin-cirrus pixels. Since the clouds and earth surface have different reflectance spectra in the visible and near-infrared frequencies, a fast cloud detection method involving AHI 0.47-, 0.64 and 0.86-μm channels (Zhuge et al., 2017) is used to distinguish cloudy pixels from clear-sky pixels. After that, thin cirrus pixels are discarded if the normalized reflectance of 0.47-μm visible channel is lower than 0.35. During nighttime when visible and near-infrared data are unavailable, the clear-sky and thin-cirrus pixels are removed if (i) the observed brightness temperature at 10.4 μm at the target pixel is
less than 5 K colder than the warmest pixel within the entire Fujian domain; (ii) the BTD between 10.4- and 12.4-μm (i.e., $T_{b,10.4} - T_{b,12.4}$) at the target pixel is 0.6 K greater than the BTD value at the warmest pixel within the 19×19 pixel box centered at the target pixel; or (iii) the BTD between 8.7- and 12.4-μm (i.e., $T_{b,8.7} - T_{b,12.4}$) is 1.6 K greater than the BTD value at the warmest pixel within the 19×19 pixel box centered at the target pixel. The (ii) and (iii) checks are used for detecting thin cirrus clouds, which were introduced by Krebs et al. (2007).

In the second step, all the contiguous thick cloud pixels are grouped into individual “cloud objects” using the connected-component labeling technique proposed by Abubaker et al. (2008). The -20°C threshold for the 10.4-μm infrared channel is then employed to separate the immature cumulus objects from the thunderstorm objects. The thick clouds that have the highest cloud top colder than -20°C may have begun to precipitate, and are thus classified as thunderstorms.

Obviously, the cumulus cloud mask algorithm is significantly improved over the SATCAST algorithm (Walker et al., 2012). Firstly, the thick-cloud pixel identification is used instead of the cloud type products so that the CI nowcasting algorithm is independent of ancillary data. Secondly, the removal of thunderstorms is conducted after the cloud object identification. By doing so, a misclassification of cirrus anvil and/or cloud edge of a thunderstorm, which could have a BT value higher than -20°C, as an individual cumulus is avoided.

### 3.2 Cumulus-object Tracking

In order to monitor the 10-min evolutions of cloud-top properties from the previous time
(chronologically labeled for T1) to the current time (T2), one needs to know the cloud object at T2 that developed from the cloud object at T1. The “temporal overlapping” method proposed by Zinner et al. (2008) and illustrated in Fig. 3 is adopted for tracking the cumulus objects from T1 to T2. A GOES imager scans the earth every 15~30 min during which time a cumulus cloud would move far away from the position at T1. In order to find an overlap of a T1 object with a T2 object, the atmospheric motion vectors were used to advect any T1 object to a forecast position at T2 (Walker et al., 2012). Given a 10-min AHI refresh rate, the atmospheric motion vectors are not crucial in the new algorithm. The reason is the following: Assuming a wind speed of 5 m s\(^{-1}\) that is appropriate in most conditions, a cumulus cloud would move to a position 3 km (or 6 pixels) away in 10 min with this speed. Since the equivalent diameter of a cumulus object is larger than 3 km most of time, an overlap between T1 and T2 objects would exist even though the T1 object is not advected.

### 3.3 CI Forecast Determinations

The procedure of CI forecast determinations is similar to that in the SATCAST algorithm except for the selected predictors and corresponding thresholds. The CI nowcastings are provided using a binary, deterministic approach with several satellite-based CI predictors associated with the cloud top properties. When a majority of the CI predictors meet their thresholds, CI is likely to occur within the next 0-2 h and thus a positive CI forecast is assigned for the cloud object, or else, a null forecast is assigned. To avoid the blurring of the spectral signals, the magnitudes of CI predictors are estimated using an average of the 25% of pixels with the coldest values of \(T_{b,10.4}\) within a target cloud object.

The CI predictors finally used for CI forecasts were selected from 12 infrared and visible
interest fields listed in Table 3. The selection is based on the distributions of 12 interest fields for the 35 CI events that did not undergo significant splitting or merging. The distributions are different at different time prior to the CI occurrence. To help understanding the cumulus evolution prior to CI occurrences, the distributions of the 12 interest fields during the period from $t_0$-60min to $t_0$ at a 10-min interval will be shown below (Figs. 4-6), where $t_0$ is defined as the most recent AHI scan time before a CI occurrence. In other words, if a CI occurred at 0136 UTC, then $t_0$ is set to 0130 UTC.

Figures 4 and 5 depict the distributions of 12 interest fields. The cloud-top height, indicated by $T_{b,10.4}$ (Fig. 4h) exhibits a monotonically increasing trend. Apparently, CI often occurred in Fujian with a warm-rain process, since the cloud-top at $t_0$ is still warmer than 0°C (i.e., 273.15 K) for most CI events. It can also be inferred that the upper- and mid-tropospheric water vapor contents did not undergo many changes prior to CI occurrences (Fig. 4e and 4f). The values of $T_{b,7.3}$ (Fig. 4g) and $T_{b,6.9}-T_{b,7.3}$ (Fig. 5c) began to change 20 min prior to a CI occurrence, indicating that the cloud top is elevated to ~600hPa. The cloud optical thickness indicated by both $\rho_{0.47}$ (Fig. 4a) and $T_{b,12.4}-T_{b,10.4}$ (Fig. 5b), as well as the cloud-top phase indicated by $T_{b,8.6}+T_{b,12.4}-2T_{b,10.4}$ (Fig. 5d), also show an increasing trend, which suggests that the cloud gradually deepened and the cloud top was gradually glaciated before the CI occurrence. However, the particle size indicated by the three near-infrared or mid-infrared interest fields, $\rho_{1.6}$ (Fig. 4b), $\rho_{2.3}$ (Fig. 4c), and $\rho_{3.9}$ (Fig. 4d), did not show a consistent trend. The trends for $\rho_{1.6}$ (Fig. 4b) and $\rho_{2.3}$ (Fig. 4c) are not monotonic, but the trend for $\rho_{3.9}$ (Fig. 4d) is. This inconsistence among the three near-infrared or mid-infrared interest fields may be caused by differences in penetration depths of the three channels. The
channel 7 (3.9μm) can only detect the upper portion of a convective cloud while the channel
5 (1.6μm) can detect the lower part. Inconsistency among the three channels may indicate
heterogeneous droplet size profile. In this study, ρ_3.9, which indicates the cloud-top particle
size, is retained. Based on the above assessments, six interest fields— ρ_0.47, ρ_3.9, T_b,10.4,
T_b,7.3-T_b,10.4, T_b,12.4-T_b,10.4, and T_b,8.6+T_b,12.4-2T_b,10.4, are finally selected as the CI predictors of
the proposed CI nowcasting algorithm. The thresholds for the six selected CI predictors are
determined based on the 25th percentile 30 min prior to the CI occurrence. This ensures that
the average forecast lead time is about 30 min long.

The cloud updraft strength, deepening rate, as well as cloud-top hydrometeor growth and
glaciation rate monitored could be assessed by examining the 10-min temporal differences of
T_b,10.4, ρ_0.47, ρ_3.9, and T_b,8.6+T_b,12.4-2T_b,10.4 (Fig. 6). A weak updraft with a strength around
-1K/10min is found for most CI events (Fig. 6c). For most CI events, the updraft became
stronger 20 min prior to CI occurrences, and reached a peak value of -4K/10min when CI
occurs. Similarly, the particle size growth had been slow in the earlier stage and faster when
the cloud developed into a CI (Fig. 6b). Exceptions are found for about 25% of CI events to
experience negative updrafts and particle size growths. Since the rates of variations of both
the cloud optical thickness and cloud-top phase are not regular (Fig. 6a and 6d), only the
10-min temporal differences of T_b,10.4 and ρ_3.9 are taken as the two CI predictors in addition to
the above six selected CI predictors (Table 4).

At the last step of CI forecast determination, a cumulus object will get a positive CI
forecast if a decreasing T_b,10.4 or ρ_3.9 is observed during a 10- min time period and at least five
of the eight CI predictors need to meet their thresholds. Table 5 gives the PODs as functions
as the number of CI predictors meeting their thresholds, where POD is defined as the fraction
of CI events that are correctly forecasted. To ensure the POD be greater than 75% at 30 min
prior to CI, at least five CI predictors seem to be an “optimal” choice. During nighttime, $\rho_{0.47}$
and $\rho_{3.9}$ are not available, and at least three of the five CI predictors meeting their thresholds
(Table 6) for a positive CI forecast.

4. Validation

4.1 Case Study

The CI nowcasting algorithm is applied to a case on 1 August 2015 over the northern
part of Fujian, China. This CI case represents a typical summertime convective process over
Southeastern China. The CI events initially began in the morning under a clear-sky condition,
and developed into two severe multi-cell thunderstorms in the late afternoon (Fig. 7). We
may focus our attention on the time period from 0000 to 0300 UTC during which the earliest
15 CI events were triggered. Figure 8 presents six composite reflectivity radar images from
0200 UTC to 0300 UTC at a 12-min interval, along with the CIs determined by radar images.
The radar images at 0206, 0218, 0230, 0242 and 0254 UTC were not presented but the CIs
determined by radar images at these times are shown as dashed circles. As seen from these
radar images, two echoes with reflectivity intensities greater than 35 dBZ appeared at 0218
UTC, indicating the eruptions of the first two CI events. The number of intense echoes
increased rapidly with time. By 0300 UTC, 15 CI events were observed, which are marked
with solid or dashed circles on the radar images in Fig. 8f.

The AHI/Himawari-8 multispectral observations with a 10-min temporal resolution are
used to monitor the cumulus developments. To help understand how the CI algorithm works,
two CI events, which are labeled as “A” and “B” in Fig. 8, are analyzed in more detail (Fig. 9). Both events took place at about 0220 UTC. The first prediction of event “A” is at 0050 UTC, preceding the actual occurrence by 88 min; while the first prediction of event “B” is at 0200 UTC, only preceding the actual occurrence by 24 min. The precursor of CI event “A”, hereafter cumulus “A”, began with a relatively strong updraft around -2 K/10min. The cloud-top temperature dropped below 10°C at 0040 UTC. After that, cumulus “A” developed slowly, along with merging and splitting. A rapid growth of cumulus “A” was restored at 0150 UTC, with a strength about -5 K/10min. Since five or more CI predictors satisfy their thresholds, a positive CI forecast is assigned for cumulus “A” beginning at time 0050 UTC. In contrast, cumulus “B” developed slowly at the very beginning. The cloud top temperature did not drop below 10°C until 0200 UTC. The cloud-top cooling rate was about -3 K/10min. When the S-band CINRAD radar detected a CI signal, the cloud top of cumulus “B” was still warmer than 0°C, indicating the associated precipitation resulted from a warm-rain process.

The CI forecasts determined by AHI/Himawari-8 from 0040 UTC to 0230 UTC on 1 August 2015 at a 10 min interval are shown in Fig. 10. The first positive CI forecast was assigned on the images at 0040 UTC, and verified by the CI event that occurred at 0242 UTC. The forecast lead time for this event is 122 min. Out of the 15 CI events at 0230 UTC, 13 were successfully predicted. The POD for this case is 93.33%. The CI event that is labeled as “C” in Fig. 8 is not predicted by the CI nowcasting algorithm. We find that the cloud top temperature of cumulus “C” remained warmer than 10°C even though the 35-dBZ echo was detected by the S-band CINRAD radar. By examining the rain observations from the rain-gauge stations and the sequence cloud development based on the AHI images (figure
omitted), the CI signal of cumulus “C” might be inferred as a noise. The CI event “D” is missed at 0230 UTC, but predicted at 0250 UTC. This is due to the fact that AHI did not provide measurements at 0240 UTC. Otherwise, it could be predicted as early as 0240 UTC, to give a 14-min forecast lead time. The AHI-based CI algorithm also produces seven false alarms, with a FAR of 33.33%. Here, FAR is defined as the fraction of positive CI nowcasts that are finally flagged as false alarms. Among the seven false alarms, three were repeated twice. Most of them exhibited a short-lived updraft at the early stage, and were soon suppressed by a mid-level capping inversion. Therefore, although other predictors satisfied their thresholds, the capping inversion predictor $T_{b,7.3} - T_{b,10.4}$ is still lower than the -26-K threshold.

4.2 Average performance

A total of 216 CI events during the period from July to September 2015 over Fujian are used to obtain an average performance of the AHI-based CI nowcasting algorithm employed in this study. These CI events took place either from clear-sky conditions, as presented in section 4.1, or from convectively active conditions. The statistical results demonstrate that the algorithm has good skill in capturing the cumulus development and predicting the CI occurrences. During daytime (nighttime), only 5 (2) CI events, accounting for 3.18% (3.39%) of the CI events, are missed by the CI algorithm; meanwhile, 102 (69) false alarms are produced. The PODs for the AHI-based CI algorithm is 96.82% and 96.61%, and the FARs are 40.16% and 54.76% at daytime and nighttime, respectively. The forecast lead time ranges from 14 min to more than 120 min. If the cumulus object continually develops with a rapid rate, the lead time will be short. On the contrary, if the cumulus grows slowly after the
cloud-top temperature dropped below 10°C, the early detection of CI will be relatively easy and the lead time will be long. Another possible reason for a long lead-time of CI forecast algorithm is the mountain slope. After a shallow cumulus cloud is initiated, the mountain slopes may anchor the location of shallow cumulus that will deepen one hour or longer. A slower decrease of $T_{b,10.4}$ is accompanied with a sub-pixel accumulation or an enhancement of these shallow cumulus. This explanation is more credible when considering typical lifetimes of individual deep convective clouds. The frequencies of correctly predicted CI events at different forecast lead times are presented in Fig. 11. Apparently, the CI nowcastings with a lead time between 20 and 80 min are mostly populated. The average CI forecast lead time for the CI nowcasting algorithm is ~64 min, with a median value of 60 min.

5. Summary and Conclusions

Benefiting from high spatial- and temporal-resolution, and multi-spectral measurements of the AHI instrument on board Himawari-8, the CI nowcasting algorithm is improved in the following three aspects: 1) cumulus cloud mask, 2) cumulus-object tracking, and 3) CI forecast determination. The AHI-based CI algorithm is independent of any dynamic ancillary data, such as the cloud type and atmospheric motion vector products, and is able to process the input data and generate CI forecasts immediately once the latest AHI data are received.

In order to make sure that the AHI-based CI algorithm is applicable to CIs in sub-tropical regions, this study assessed 12 interest fields including the visible and near-infrared reflectance, infrared water vapor and infrared window BTs, and dual- and triple-channel BTDs. Finally, six interest field that are relevant to the cloud optical thickness, as well as cloud-top height, partial size and glaciation, were selected to diagnose the developmental
level of a certain cumulus. The temporal differences of cloud-top height and partial size are selected to help diagnose whether a cumulus is growing. By using these eight CI predictors, the AHI-based algorithm is skillful in predicting the CI occurrences associated with warm-rain processes.

Validation of the AHI-based CI nowcasting algorithm was firstly performed with a case on 1 August 2015 over Northern Fujian. In this case, a total of 15 CI events were detected during the time period 0200-0300 UTC by a network of S-band CINRAD radars. The CI algorithm successfully predicted 14 CI events and meanwhile produced 7 false alarms. The POD and FAR for this case are 93.33% and 33.33%, respectively. Then, a total of 216 CI events that occurred during the three-month period from July to September 2015 over Fujian are used to assess the average performance of the AHI-based CI algorithm. The averaged PODs are as high as 96.82% and 96.61% at daytime and nighttime, respectively. The forecast lead time ranged from 14 to 120 min. The mean forecast lead time is ~64 min.

In the future, we will improve the AHI-based CI algorithm by further reducing false alarms. The current version of the CI algorithm treats each CI predictor equally. False-alarm forecasts might be generated when several relatively less sensitive predictors meet their thresholds while others don’t (Lee et al., 2017). To avoid this from happening, the relative importance (weights) of different CI predictors will be computed by using the linear discriminant analysis (Wilks, 2006). All CI predictors will be weighted and then summed to give a set of probabilistic forecasts (i.e., 0-100%).

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Table 1. Dates, time periods and number of CI events per day. A CI event is determined by the composite reflectivity radar images over Fujian, China. Local times are UTC+8h for Fujian.

| Date     | CI times (UTC) | CI events | Date     | CI times (UTC) | CI events |
|----------|----------------|-----------|----------|----------------|-----------|
| July 10  | 0810           | 1         | August 1 | 0210-1310      | 24        |
| July 11  | 0840           | 1         | August 2 | 0250-1130      | 11        |
| July 13  | 0320-0850      | 13        | August 3 | 0510-1300      | 17        |
| July 14  | 0220-1740      | 14        | August 4 | 0330-2230      | 24        |
| July 15  | 0250-1740      | 9         | August 5 | 0300-1810      | 26        |
| July 17  | 0250-0320      | 2         | August 6 | 0510-0700      | 6         |
| July 18  | 0540-0820      | 4         | August 7 | 0440-0830      | 8         |
| July 19  | 0740-0810      | 3         | August 21| 0930-1250      | 3         |
| July 26  | 0850-0920      | 3         | September 5 | 0300-0410    | 4         |
| July 27  | 0410-0600      | 4         | September 7| 0600-0610    | 2         |
| July 28  | 0210-0550      | 8         | September 8| 0740-0910    | 2         |
| July 29  | 0130-0410      | 4         | September 16| 0920-0940    | 3         |
| July 30  | 0340-1000      | 9         | September 23| 0440-0620    | 3         |
| July 31  | 0310-0630      | 8         |          |                |           |
Table 2. Central wavelengths, sub-satellite resolutions and main gaseous absorbers of AHI visible, near-infrared and thermal infrared channels. The channels used in the CI nowcasting algorithm are also indicated.

| Channel      | Central wavelength | Resolution | Main gaseous absorber               | Used in algorithm |
|--------------|--------------------|------------|-------------------------------------|-------------------|
| Visible*     |                    |            |                                     |                   |
| 1            | 0.47 μm            | 1.0 km     |                                     | a, c              |
| 2            | 0.51 μm            | 1.0 km     |                                     | -                 |
| 3            | 0.64 μm            | 0.5 km     |                                     | a                 |
| Near-infrared* |                  |            |                                     |                   |
| 4            | 0.86 μm            | 1.0 km     |                                     | a                 |
| 5            | 1.6 μm             | 2.0 km     |                                     | -                 |
| 6            | 2.3 μm             | 2.0 km     |                                     | -                 |
| Infrared     |                    |            |                                     |                   |
| 7            | 3.9 μm             | 2.0 km     | Window                              | a, c              |
| 8            | 6.2 μm             | 2.0 km     | Upper-troposphere water vapor       | -                 |
| 9            | 6.9 μm             | 2.0 km     | Mid-troposphere water vapor         | -                 |
| 10           | 7.3 μm             | 2.0 km     | Lower-troposphere water vapor       | c                 |
| 11           | 8.6 μm             | 2.0 km     | Window                              | a, c              |
| 12           | 9.6 μm             | 2.0 km     | Ozone                               | -                 |
| 13           | 10.4 μm            | 2.0 km     | Window                              | a, b, c           |
| 14           | 11.2 μm            | 2.0 km     | Window                              | -                 |
| 15           | 12.4 μm            | 2.0 km     | Window                              | a, c              |
| 16           | 13.3 μm            | 2.0 km     | Carbon dioxide                      | c                 |

* only available during daytimes
a used in cumulus cloud mask
b used in cumulus-object tracking
c used in CI Forecast Determination
Table 3. List of interest fields that were tested for the CI forecast, along with their definitions and physical relationships to convective clouds.

| Abbreviation | Definition | Physical basis |
|--------------|------------|----------------|
| $\rho_{0.47}$ | Channel-1 Reflectance | Cloud optical thickness |
| $\rho_{1.6}$  | Channel-5 Reflectance | Cloud-top glaciation, particle size |
| $\rho_{2.3}$  | Channel-6 Reflectance | |
| $\rho_{3.9}$  | Channel-7 Reflectance | |
| $T_{b,6.2}$  | Channel-8 brightness temperature | Upper-tropospheric water vapor content |
| $T_{b,6.9}$  | Channel-9 brightness temperature | Mid-tropospheric water vapor content |
| $T_{b,7.3}$  | Channel-10 brightness temperature | Lower-tropospheric water vapor content |
| $T_{b,10.4}$ | Channel-13 brightness temperature | Cloud-top height |
| $T_{b,7.3}-T_{b,10.4}$ | Brightness temperature difference between channels 10 and 13 | Cloud-top height relative to lower-troposphere (~600 hPa) |
| $T_{b,12.4}-T_{b,10.4}$ | Brightness temperature difference between channels 15 and 13 | Cloud optical thickness |
| $T_{b,6.9}-T_{b,7.3}$ | Brightness temperature difference between channels 9 and 10 | Cloud-top height relative to mid-troposphere (~450 hPa) |
| $T_{b,8.6}+T_{b,12.4}-2T_{b,10.4}$ | Tri-channel difference of Channels 11, 15 and 13 | Cloud-top phrase |
Table 4. Eight CI predictors finally selected for the CI nowcasting and their thresholds.

| CI predictors | Threshold | Available during |
|---------------|-----------|------------------|
| $\rho_{0.47}$ | >50.0%    | daytime          |
| $\rho_{3.9}$  | <40.0%    | daytime          |
| $T_{b,10.4}$  | <283.15K  | all-day          |
| $T_{b,7.3}-T_{b,10.4}$ | >-26.0K | all-day          |
| $T_{b,12.4}-T_{b,10.4}$ | >-3.5K  | all-day          |
| $T_{b,12.4}+T_{b,12.4}-2T_{b,10.4}$ | >-6.0°C | all-day          |
| 10-min temporal difference of $\rho_{3.9}$ | <0.0%    | daytime          |
| 10-min temporal difference of $T_{b,10.4}$ | <0.0K    | all-day          |
Table 5. PODs (unit: %) as a function of the number of CI predictors meeting their thresholds during daytime.

|                  | >=1 | >=2 | >=3 | >=4 | >=5 | >=6 | >=7 |     |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| 0min prior to CI | 100 | 100 | 100 | 100 | 100 | 96.97 | 66.67 |     |
| 10min prior to CI| 100 | 100 | 100 | 100 | 93.55 | 93.55 | 83.87 | 58.06 |
| 20min prior to CI| 100 | 100 | 100 | 93.10 | 89.66 | 86.21 | 68.96 | 44.83 |
| 30min prior to CI| 100 | 96.43 | 92.86 | 89.29 | 78.57 | 71.43 | 53.57 | 32.14 |
| 40min prior to CI| 96.67 | 96.67 | 86.67 | 80.00 | 76.67 | 56.67 | 30.00 | 23.33 |
| 50min prior to CI| 100 | 88.46 | 73.08 | 61.54 | 53.85 | 42.31 | 26.92 | 7.69  |
Table 6. Same as Table 5, except for nighttime using only infrared predictors.

| Time before CI | >=1 | >=2 | >=3 | >=4 | 5   |
|----------------|-----|-----|-----|-----|-----|
| 0min prior to CI | 100 | 100 | 100 | 96.97 | 84.85 |
| 10min prior to CI | 100 | 100 | 96.77 | 87.10 | 77.42 |
| 20min prior to CI | 100 | 96.55 | 89.66 | 72.41 | 48.28 |
| 30min prior to CI | 92.86 | 89.29 | 78.57 | 67.86 | 39.29 |
| 40min prior to CI | 93.33 | 83.33 | 73.33 | 53.33 | 30.00 |
| 50min prior to CI | 96.15 | 69.23 | 57.69 | 38.46 | 11.54 |
**Caption list**

Fig. 1. Spatial locations of CINRAD radars and the topography (unit: m) over Fujian, China.

Fig. 2. Flowchart of the cumulus mask algorithm.

Fig. 3. Schematic illustration of the cumulus-object-tracking method. Each cumulus object at the current time (orange) is assigned an ID number, and then the positions of the cumulus objects 10 min earlier (blue) are compared with those at the current time. When an overlap exists, the same ID numbers associated with the current-time objects are assigned to the previous-time objects. Otherwise, the current-time object is a newborn, or the previous-time object has dissipated or grown into a thunderstorm object.

Fig. 4. Distributions of the interest fields of (a) $\rho_{0.47}$, (b) $\rho_{1.6}$, (c) $\rho_{2.3}$, (d) $\rho_{3.9}$, (e) $T_{b,6.2}$, (f) $T_{b,6.9}$, (g) $T_{b,7.3}$, and (h) $T_{b,10.4}$ at different time prior to CI occurrence. The gray times signs represent CI events used in this study. The blue box edges indicate the 25th and 75th percentiles, and the red line indicates the median value.

Fig. 5. Same as Fig. 4 except for (a) $T_{b,7.3}$-$T_{b,10.4}$, (b) $T_{b,12.4}$-$T_{b,10.4}$, (c) $T_{b,6.9}$-$T_{b,7.3}$, and (d) tri-spectral difference.

Fig. 6. Distributions of the 10-min temporal differences of (a) $\rho_{0.47}$, (b) $\rho_{3.9}$, (c) $T_{b,10.4}$, and (d) tri-spectral difference at different times prior to CI occurrence. The gray circles represent CI events. The blue box edges indicate the 25th and 75th percentiles, and the red line indicates the median value.

Fig. 7. Red-Green-Blue (RGB) composite images of AHI channels 3, 2 and 1 at (a) 0100 and (b) 0700 UTC on 1 August 2015 over Fujian, China. Local times are the UTC times plus 8 hours in Fujian.
Fig. 8. Composite radar images of reflectivity (unit: dBZ) at (a) 0200, (b) 0212, (c) 0224, (d) 0236, (e) 0248, and (f) 0300 UTC on 1 August 2015 over northern Fujian, China. The CIs determined by radar images are shown as circles. The occurrence time (unit: UTC) of CI events is indicated by colors and line styles according to the legend. The CI events labeled for “A”, “B”, “C”, and “D” will be discussed later.

Fig. 9. Temporal variations of the CI interest fields (a) $\rho_{0.47}$, (b) $\rho_{3.9}$, (c) $T_b,10.4$, (d) $T_b,7.3-T_b,10.4$, (e) $T_b,12.4-T_b,10.4$, and (f) tri-spectral difference for CI events A (red) and B (blue) indicated in Fig. 8. Red and blue dashed lines indicate the interval when the cloud objects were splitting or merging. The threshold for each predictor is shown with dashed black line.

Fig. 10. CI forecasts determined by the AHI/Himawari-8 at (a) 0040, (b) 0050, (c) 0100, (d) 0110, (e) 0120, (f) 0130, (g) 0140, (h) 0150, (i) 0200, (j) 0210, (k) 0220, and (l) 0230 UTC on 1 August 2015. Gray and brown cloud objects are thunderstorm and cirrus, respectively. The blue cumulus objects represent positive CI forecasts, and the green cumulus objects represent the null forecasts. The hits and false alarms are shown as circles and squares, respectively. The actual occurrence time of CI events is indicated by colors and line styles according to the legend. The positive CI forecasts, if not overlaid with cycles or squares, are also hits that were verified by the radar echoes at 0306-0400 UTC.

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