FORECASTERS' FORUM

On the Construction Principle of Conceptual Models for Severe Convective Weather Forecasting Operations in China

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ABSTRACT

It is argued here that even with the development of objective algorithms, convection-allowing numerical models, and artificial intelligence/machine learning, conceptual models will still be useful for forecasters until all these methods can fully satisfy the forecast requirements in the future. Conceptual models can help forecasters form forecast ideas quickly. They also can make up for the deficiencies of the numerical model and other objective methods. Furthermore, they can help forecasters understand the weather, and then help the forecasters lock in on the key features affecting the forecast as soon as possible. Ultimately, conceptual models can help the forecaster serve the end users faster, and better understand the forecast results during the service process. Based on the above considerations, construction of new conceptual models should have the following characteristics: 1) be guided by purpose, 2) focus on improving the ability of forecasters, 3) have multiangle consideration, 4) have multiscale fusion, and 5) need to be tested and corrected continuously. The traditional conceptual models used for forecasts of severe convective weather should be replaced gradually by new models that incorporate these principles.

1. Introduction

Conceptual models that are built from events having a similar outcome (i.e., analogs) are effective at diagnosing the synoptic and mesobeta environments associated with weather events (e.g., Moore et al. 2003; Novak et al. 2004, 2010; Stuart et al. 2007). For example, in East Asia, there are five types of evolving weather patterns that help determine cold-air outbreaks: development of a low-amplitude trough; eastward movement of a low pressure trough; a trough that becomes inverted; a zonal circulation; and a “rotating” low pressure, respectively (Zhu et al. 2007). For severe convective weather, the conceptual models must account for the geographical area of the convective weather, the location of initial

convective development, the convective trigger mechanism, the mode of subsequent convective development, and then the duration of the convective activity (e.g., Miller 1972; Crisp 1979). In China, severe convective weather conceptual models are often classified according to weather conditions at stations in various provinces and cities. These conceptual models are mainly based on characteristics of the 500-mb pattern (1 mb = 1 hPa), and occasionally on the 850-mb pattern, and then subdivided according to the type of severe convective weather (Zhang 2011). These conceptual models help the forecaster quickly understand and identify the larger-scale patterns associated with severe convective weather and guide the subsequent forecast process. However, they can be difficult to develop. First, their construction lacks unified guiding principles, leading to deficiencies in usability. Second, although there may be a specific conceptual model for severe hail, for example, other kinds of severe convective weather can have similar atmospheric conditions. Thus, because of these ambiguities,

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it can be difficult to assign a specific weather classification to a specific convective weather hazard.

Recently, in operational forecasting centers in China, and elsewhere around the world, the role of human forecasters has been challenged in favor of applications of artificial intelligence (AI)/machine learning approaches. How to maintain the role of the forecaster in future forecasting has been discussed (Stuart et al. 2006, 2007) and will likely evolve the role of the conceptual model in the forecasting process. Convection-allowing model (CAM) usage at the National Meteorological Center of China Meteorological Administration (CMA) began in 2014.¹ Accordingly, the period of CAM evaluation has been relatively short and forecasters have only had a limited amount of time to fully understand the strengths and weaknesses of CAMs. An analogous statement can be made regarding AI/machine learning approaches and the ability to make these skillful. Complicating both endeavors is the fact that CAMs are constantly being improved. In contrast, time-consistent data (as well as coarser-resolution models) have been available for multiple decades and have been allowed for the foundation of conceptual models. The suggestion here is that a forecaster would have more confidence in a conceptual model, because it is based on a longer record of data. As we will discuss, numerical models and machine learning approaches can be still limited in their ability to predict severe convective weather.

In this paper, the authors try to explain that the construction and use of the conceptual model are still valuable for China's severe convective weather prediction and provide the principles of conceptual model use and their construction from the perspective of forecasters in China. Since China is located in the Asian monsoon region, the construction principles of the conceptual model proposed here can also be used as a reference for forecasters in other countries with similar climatic backgrounds in the same monsoon region. In addition, forecasters in other countries can also refer to the construction principles of conceptual models if they encounter similar situations with deficiencies of objective algorithms and numerical models mentioned in this paper. Most of the construction principles mentioned here are related to the design principles of the conceptual model and can be used as a reference for forecasters in other regions. Before discussing the principles of conceptual model construction, it is necessary to discuss whether

the conceptual model and human forecaster are useful. Since it is difficult to measure the value of the conceptual model, we have to discuss whether the forecaster who uses it has the value of existence. Therefore, in sections 2 and 3, threat scores between human forecasters and AI/machine learning techniques are compared. Furthermore, we describe the use of conceptual models for severe convective weather forecasting in China, which serve not only as a means for pattern recognition, but also as a reflection of the internal physical mechanisms and the interaction between different scales; thus, they help make the forecast process smooth and facilitate user-oriented explanations of the forecast. Next, in section 4, we provide examples of conceptual model construction, give suggestions on how to create new conceptual models, and update existing ones. Concluding remarks are given in section 5.

2. The challenge of the development of objective algorithms to the conceptual model

Stuart et al. (2007) mentioned that if forecasters continue to make only minimal improvements over products such as model output statistics (MOS), humans may eventually disappear from the forecasting process. However, when computer and objective algorithms are not mature enough to predict weather threats at critical times (such as inclement and extreme weather), the existence of meteorologists is crucial in an increasingly automated working environment and must continue for the foreseeable future (Stuart et al. 2006). Roberts et al. (2012) also suggested that prior to dissemination of nowcasts, the role of the forecaster was enhanced by the way in which the forecaster input the locations of surface convergence boundaries into an automated convective storm nowcasting system to improve the performance of the nowcasts of convective storm initiation and evolution. Therefore, the allocation of human resources for both near-term (3–12 h) forecasting duties as well as for nowcasting (0–3 h) has changed with the significant development of forecasting techniques involving AI/machine learning, which has been widely adopted in operational meteorology in recent years (Mecikalski et al. 2015; Han et al. 2015). For example, machine learning is used in radar extrapolation forecasting (Shi et al. 2015; Klein et al. 2015; Wang et al. 2017), has been applied to real-time reanalysis data for nowcasting (Han et al. 2017; Zhang et al. 2017) and radiometer observations (Das et al. 2017), and used to predict convective initiation based on meteorological satellite data (Cintineo et al. 2014; Han et al. 2015; Mecikalski et al. 2015; Cintineo et al. 2018), damaging straight line winds (Lagerquist et al. 2017), and rainfall (Yu et al. 2017). Machine learning

¹ Version 1.0 of GRAPES_Meso has been run operationally since 2006. The horizontal grid point spacing of GRAPES_Meso was reduced to 3 km in 2012, but not implemented operationally until 2014.

TABLE 1. Description of forecast scoring metrics.

Metric	Description
Hits	Event forecast to occur, and did occur
Misses	Event not forecast to occur, but did occur
False alarms	Event forecast to occur, but did not occur
$TS = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}}$	Threat score; (0–1); 0 indicates no skill, 1 indicates perfect skill
$POD = \frac{\text{hits}}{\text{hits} + \text{misses}}$	Probability of detection; (0–1); 1 indicates perfect score
$FAR = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}}$	False alarm ratio; (0–1); 0 indicates perfect score

also has been used in short-term (12–72 h) hail prediction (Gagne et al. 2015, 2017), quantitative precipitation forecasts (Gagne et al. 2014), short-term thunderstorm and rainfall forecasts (Manzato 2007), and for the calibration of probabilistic quantitative precipitation forecasts (Yuan et al. 2007). At the CMA in particular, machine learning has adopted a modified convolutional long short-term memory (LSTM) network and convolutional neural network (CNN) based on satellite, radar, NWP models, and especially CAMS, for severe convective weather nowcasting, near-term forecasting, and short-term forecasting.

To verify the performance of the constructed AI algorithm, we compared the forecasting of short-duration heavy rain by AI and different senior forecasters at the National Meteorological Center of CMA. The comparison results in July and September 2017 were analyzed and discussed as an example. Since the AI algorithm was run for only three months during July–September in 2017, if we would like to compare the predictions of machine learning and human forecasters in detail for the entire warm season (from April to September), the data in 2018 would be better to be used.

An obvious question when discussing machine learning is how well it performs. A partial answer is given by comparing verification scores (see Table 1 for descriptions) for short-duration heavy rain in July and September 2017 (Fig. 1) of some senior forecasters and machine learning forecasts in the CMA. These show that machine learning in the CMA, as applied to severe convective weather, often performs better than human forecasters. From this conclusion, the role of the forecaster (or subjective forecasting) seems to be inferior to that of AI technology, and the utility of the conceptual model often used by the forecaster (or in subjective forecasting) as a predictive aid seems to be relatively low.

However, after further analysis of Fig. 1 and Table 2, we find that although the average threat score (TS; see

FIG. 1. The threat scores (TSs; see Table 1) of six senior forecasters and those of machine learning for short-duration heavy rain at the National Meteorological Center of CMA in July 2017; (b) as in (a), but for September 2017.

Table 1 for description) of AI is higher than that of forecasters it is not higher than that of all forecasters, and not always higher in every situation. For example, the TS of AI (0.304) was higher than that of forecasters (0.273) for forecasts of short-duration heavy rain issued from 0000 UTC in 2018. While, for thunderstorms (AI: 0.362; human forecaster: 0.373) and thunderstorm gale and hail (AI: 0.038; human forecaster: 0.043), the TSs of AI are lower than those of the forecaster (Table 2). Forecasters issue operational forecasts three times a day for three types of severe convective weather (thunderstorm, short-duration heavy rain, thunderstorm gale and hail) at the National Meteorological Center of CMA. We would like to know whether the comparison results of TSs for short-duration heavy rain issued from 0600 UTC, 1200 UTC, and in a whole day are the same as the result for 0000 UTC. Consider the composite score of forecasts of short-duration heavy rain (rainfall amounts $\geq 20 \text{ mm h}^{-1}$) from April to September 2018 (Table 3). TS of AI is significantly higher than that of forecasters only in July in which the forecasts are issued at 0000 UTC, while the TSs of the forecasters are significantly higher than those of AI in April and September in which the forecasts are issued at 0600 and 1200 UTC. Furthermore, the TSs of forecasters are also higher than those of AI significantly in June in which the forecasts are issued at 0600 UTC. When the whole-day

TABLE 2. Severe convective weather near-term forecast scores for events during 0000–1200 UTC and forecasts issued from 0000 UTC at the National Meteorological Center of CMA in 2018. Probability of detection (POD), false alarm ratio (FAR), and threat score (TS) (see Table 1) values are given.

Convective weather	Machine learning			TS of forecaster		
	POD	FAR	TS	POD	FAR	TS
Short-duration heavy rain	0.580	0.611	0.304	0.360	0.471	0.273
Thunderstorm	0.676	0.562	0.362	0.736	0.569	0.373
Thunderstorm gale and hail	0.084	0.902	0.038	0.108	0.929	0.043

precipitation forecast was taken into account, the forecaster's score is significantly higher than that of AI in April, June, and September. The differences in other months are not as significant. This shows that AI does not always perform better than human forecasters. The AI algorithms mentioned here are trained based on observational data and numerical model output, which may affect the performance of the AI algorithm. In addition to the disadvantages of the AI algorithm, the deficiency of the numerical model and the fluctuation of the numerical model performance may affect the prediction performance of the AI algorithm. On the other hand, extreme severe convection is still a relatively low probability event and the construction of AI algorithms require a large sample, which may be the reasons AI does not always perform better than the forecaster. This needs further research.

We note the conceptual model is primarily used by the forecaster in the process of forecasting and service. If the human forecaster has a positive effect on the forecast, there is an opportunity for the conceptual model to have a positive effect on the forecast. Moreover, human forecasts of convective weather mainly rely on the analysis of convective-environment conditions and the objective forecast products based on the meso- and microscale. This also provides the space and possibility for the development of conceptual model work.

3. The importance and necessity of the conceptual model for severe convective weather forecasting services

Although developments in AI/machine learning have, to some extent, reduced the need for the traditional synoptic conceptual model, the severe convective weather conceptual model remains important and necessary. In addition to using them as an auxiliary judgment for the occurrence and intensity of severe convective weather, conceptual models can also serve the following roles.

a. Help forecasters make judgments quickly

Conceptual models can guide the forecaster, especially when objective algorithms and numerical models cannot fully play their role (as will be discussed in the next subsection). A forecaster can analyze model output and use conceptual models to improve the forecast process by identifying high-impact events. It is well known that, in addition to relying on numerical prediction models and objective algorithms, forecasters use the ingredients-based method (Doswell et al. 1996) to forecast severe convective weather. When model ensemble results have high uncertainty, the forecaster can identify the key factors quickly and make decisions by using conceptual models. Take the forecasts of thunderstorm gale and hail in northwest China, for example. For the ensemble-predicted location of radar echoes and corresponding

TABLE 3. Short-duration heavy rain forecast scores at the National Meteorological Center of CMA from April to September 2018. The asterisk, double asterisk, and triple asterisk indicate that the forecast difference for that month at the 99%, 95%, and 90% level, respectively, according to the Mann–Whitney U test. The monthly forecast differences without asterisks did not pass the significance test. HF is a human forecaster. TS_{00} is the TS of short-duration heavy rain forecast scores for events during 0000–1200 UTC and forecasts issued from 0000 UTC at the National Meteorological Center of CMA from April to September 2018. TS_{06} is same as TS_{00} , but for events during 0600 UTC, on day 2 at 0000 UTC, and forecasts issued at 0600 UTC day 1. TS_{12} is same as TS_{00} , but for events during 1200 UTC day 1–1200 UTC day 2 and forecasts issued at 1200 UTC day 1. TS_A is same as TS_{00} , but for the whole daily short-duration heavy rain forecasts, which are issued at 0000, 0600, and 1200 UTC, respectively.

	April		May		June		July		August		September	
	AI	HF	AI	HF	AI	HF	AI	HF	AI	HF	AI	HF
TS_{00}	0.159	0.165	0.317	0.266	0.286	0.277	0.328**	0.281**	0.354	0.284	0.269	0.289
TS_{06}	0.101***	0.126***	0.218	0.232	0.209**	0.256**	0.226	0.236	0.250	0.259	0.148*	0.215*
TS_{12}	0.128***	0.158***	0.325	0.268	0.308	0.268	0.353	0.257	0.392	0.246	0.253**	0.262**
TS_A	0.158*	0.174*	0.278	0.269	0.254***	0.278***	0.268	0.255	0.284	0.258	0.217*	0.255*

precipitation, the uncertainty of the ensemble forecast is high, and the accuracy is low. When low-level forcing, low precipitable water (e.g., 15–20 mm), and relatively low convective available potential energy (CAPE; e.g., 200–500 J kg⁻¹) are presented, the conceptual model can identify the average thresholds suitable for local prediction conditions (such as the possibility of the lower-level dryness and the strength of the trigger).

b. Make up for the deficiencies of the numerical model and other objective methods

In China, NWP models [such as Global/Regional Assimilation Prediction System (GRAPES_Meso) and WRF] are known to exhibit low skill with predicting severe convective weather under weak forcing and low precipitable water (Wan and Liu 2018). This is particularly common in northwest and northern China. In these conditions, the model-predicted low-level wind field, precipitation field, and other environmental factors related to the prediction of thunderstorms, including those with hail, do not verify well. Predictions of NWP models of severe convective weather under weak forcing in east China from March to August 2016 are based on the 11 cases. They were classified according to the main influence system and were divided into three categories. The first category is where the upper airflow is westerly, with no obvious upper-level trough, and the lower layer has weak convergence. In the second type, severe convective weather occurred in or around the subtropical high without the influence of a deep trough system. The third type featured severe convective weather that occurred in a weak low pressure region between two high pressure systems. The simulation capability of these 11 processes has been analyzed by using the GRAPES-Meso and WRF Models. For severe convective weather triggered by weak lower-level convergence (5 cases), the predicted southerly wind near the convergence line tends to be weaker than the observed wind; the accumulated precipitation tends to be overpredicted during the last 6 h of the main precipitation period, and the predicted extreme hourly precipitation lags behind the observations. This lack of agreement between the model and observations makes the forecast of the corresponding severe convective weather more difficult. Similar comments can be made regarding NWP deficiencies in the prediction of wet microbursts in China (Zheng et al. 2016a), and in tornado occurrence (including cyclone-spawned tornadoes) (Zhang et al. 2016; Zheng et al. 2016b). Therefore, the conceptual model can alleviate NWP deficiencies by providing guidance to the forecaster on the threat for severe convective weather. NWP output is clearly deficient (in some situations more than others), which provides an opportunity for a

forecaster to leverage a conceptual model instead. At present, a perfect conceptual model does not exist. Therefore, the forecaster needs to adapt the conceptual model based on his own understanding combined with statistical experience or terrain effects. For the time being, however, the contribution of forecasters to the correction of this aspect of the model is still relatively limited.

c. Serve the end users faster during the service process and better understand the forecast results

With the development of objective forecasting methods and automation, the role of forecasters in China is shifting toward the direction of near-term forecasting and forecasting services. Stuart et al. (2007) notes that forecaster in the future should partly transition from forecaster to communicator or interpreter. Conceptual models can be used by forecasters to interpret the weather scenario, and then more easily explain the basis for the weather and forecast. In addition, forecasters are not always required to explain their forecasts to end users. However, when the end user has difficulty understanding the forecast, they can have doubts and will likely need to obtain clarification about the forecast uncertainties. These interpretation requirements often come from public for reason of extreme weather and professional users who can obtain the results of NWP when the results of different numerical models are quite different. At this time, the conceptual model can make the forecaster's interpretation and explanation of the forecast conclusion more vivid and specific, and can help the end user quickly build a clearer weather picture related to the forecast conclusion in his mind. Conceptual models also make it unnecessary for the forecaster to present every detail of the forecasting process to the end user, but only to explain the general structure of the conclusion with the conceptual model. Of course, the question of how much such an interpretation can be reduced by using a conceptual model is difficult to answer.

4. Conceptual model construction principles for severe convective weather

This section will explain the importance of creating or modifying an existing conceptual model. For example, some Chinese forecasters tend to use flow patterns as criteria for severe convective weather occurrence. This is reasonable for “synoptically obvious” forcing and environments, but in some situations, such as conditions of weak triggers and/or relatively low precipitable water, these criteria are ineffective. Similar statements can be made for squall lines, elevated thunderstorms, and thunderstorms gales under relatively humid conditions,

which are typically handled poorly by NWP models. Work is underway on these forecast problems, and the principles that are guiding this work are as follows.

a. Guided by purpose

Conceptual models are not always used for forecasting, they can also be used as a tool for customer-based interpretation and services. Due to the availability of meteorological products, many end users can access most of the products that forecasters have access to. Therefore, forecasters can provide end users with type and intensity of severe weather along with the meteorological reasoning behind the forecast. This is important for end users with the capability to analyze meteorological data. For these end users, the forecaster can use a simple conceptual model to explain the forecast thought process. The conceptual model used here must have a slightly different emphasis than the conceptual model used for forecasting. It focuses on clarifying the forecaster thought process and not so much on guiding the forecast process. Therefore, the key point of such a conceptual model is not to let the forecaster quickly identify the key factors, but simply matching relationships similar to the schematic. But even for forecasting, the conceptual model used to predict the duration of a convective system is different from the conceptual model used to predict the severe convective weather (i.e., thunderstorm, short-duration heavy rain, thunderstorm gale or hail) will be occurring with the convective system. For example, to predict the duration of severe squall line a forecaster may need to use a conceptual model based on theoretical conditions described by Rotunno et al. (1988). In contrast, to forecast the type of hazardous weather generated by the squall line, one may need to use the conceptual model based on an ingredients-based methodology (Doswell et al. 1996). Thus, construction of the conceptual model should be guided by purpose.

To illustrate this further, consider the occurrence of linear convective systems in China. These systems often occur ahead and behind the midtropospheric trough. In the events included in Table 4, all occurred ahead of a trough except for the event at 1200 UTC 3 June 2009. The focus is on different types of severe convection weather by the squall line system (short-duration heavy rain, thunderstorm gale, or hail), then the conceptual model should be built to consider the dynamic forcing, instability, and moisture conditions that are conducive to specific types of severe convective weather. This is relevant because the severe convective weather caused by the linear convective systems behind the trough is commonly thunderstorm gale and hail, while the severe weather ahead of the trough is usually thunderstorm gale.

Convective parameters offer some insight into these differences (Table 4). If the atmosphere is supportive of deep convection but precipitable water is low (e.g., <20 mm), the resulting weather is generally thunderstorm gale and precipitation less than 20 mm h^{-1} , similar to the linear convective system that occurred at Datong in Shanxi on 16 June 2010. If the precipitable water is higher (e.g., >50 mm), the height of 0° and 20°C levels are less supportive for hail², and the resultant CAPE is low, then thunderstorm gale and short-duration heavy rain would most likely occur. This occurred with the linear convective system at Shandong on 19 July 2010 and 17 July 2009. Finally, if precipitable water is moderate (e.g., >30 mm) and the height of 0° and 20°C levels are conducive for hail, then thunderstorm gale, hail, and short-duration heavy rain are all possible. This was the case with the events on 26 July 2011 and 11 June 2011. It should be noted that in this conceptual model, the knowledge of terrain and other local characteristics are important.

b. Focus on improving the ability of forecasters

The development and application of conceptual models often helps improve the human forecast process. Therefore, to determine the development and application of conceptual models should focus on enhancing the professional knowledge and forecasting ability of forecasters. The above principles can be understood in detail from the following points. Developing a conceptual model can either deepen the understanding of the mechanism or provide guidance to the forecaster. New, or existing, conceptual models should aim to reflect the physical mechanisms and help optimize the forecast processes. This can help forecasters extract internal signals faster, speed up classification, and save time. Therefore, the establishment and update of a more refined observation network and the deepening of human understanding of the refinement mechanism of severe convective weather, the development and optimization of the conceptual model from the perspective of strengthening the role of forecaster becomes an indispensable part of this work.

c. Multiangle consideration

The multiangle mentioned here includes, but is not limited to, multidimensions in space. It also includes

² In China, regions with altitudes lower than 3 km MSL are divided in two terrain steps (first step and second step, respectively), with the altitude of 1 km MSL as the division between the steps. For hail, the heights of the 0° and 20°C levels would tend to be no more than 3504 and 6646 m for the first-step terrain area, and 4184 and 7084 m for the second-step terrain area (Cao et al. 2018). For large hail (diameters > 2 cm), the heights of the 0° and 20°C layer are no more than 4300 and 7000 m, respectively (Fan and Yu 2013).

TABLE 4. Convective parameters evaluated at six sounding sites influenced by squall lines or adjacent to squall lines sounding sites before the occurrence of six squall lines.

Parameter	3 Jun 2009 (1200 UTC) Xuzhou	16 Jun 2010 (0000 UTC) Zhangjiakou	11 Jun 2011 (0000 UTC) Beijing	26 Jul 2011 (1200 UTC) Xingtai	17 Jul 2009 (0000 UTC) Zhangqiu	19 Jul 2010 (0000 UTC) Xuzhou
Convective temperature ($^{\circ}\text{C}$)	35.5	34.1	26.6	34.1	29.6	35.1
Integral of total specific humidity (g kg^{-1})	3298.9	2169.2	3005.6	4981.2	4296.6	5808
Total index	64	49	51	58	40	44
Lifting index ($^{\circ}\text{C}$)	-5.29	-1.03	-2.54	-10.83	-1.08	-2.29
Wind index	32.2	34.1	18.9	28.5	11.7	39.1
Storm relative helicity ($\text{m}^2 \text{s}^{-2}$)	2.1	2.2	2.1	0.3	0.3	2.1
Convective available potential energy (J kg^{-1})	741.4	145.8	568.5	4064.5	633.9	563.1
Convective inhibition (J kg^{-1})	314.4	572.6	127.8	45.7		159.3
Height of 0°C layer (m)	4065.4	4276.9	3450	4290	5372.5	3130
Height of -20°C layer (m)	6634.3	7076	6576	8104.6	8535	8487.5
K index ($^{\circ}\text{C}$)	38	21	34	41	36	35
Showalter index ($^{\circ}\text{C}$)	-10.02	-0.16	-1.17	-9.17	1.63	0.16
Lifting condensation level (m)	799.39	813.59	942.59	897.79	937.69	973.09
Level of free convection (m)	611.4	563.6	728.6	839.8	879.7	741.1

multiple conditions. In the past, the synoptic-scale conceptual model focused more on flow pattern recognition. However, the horizontal and vertical scales of deep convective storms are important because they are roughly proportional. This is different from the conceptual model of a synoptic-scale phenomenon, which would have a horizontal scale focus, and thus could be based primarily on the horizontal flow pattern. It is important to classify the conceptual model, one should not just think about a single level system, or dynamic condition. For example, the conceptual model of severe convective weather within the subtropical high, as discussed below, needs to consider the three-dimensional structure of the subtropical high and should not be limited to a horizontal flow pattern. The vertical influence range and the vertical inclination of the easterly wave trough should be considered in the conceptual model of the easterly wave. This is for the multidimension case. For other situations, it is not enough only to consider the multidimension. For example, the focus of the duration of linear severe convective weather is on the cold pool and the vertical wind shear over the lowest $\sim 2\text{--}3$ km.

We can demonstrate this principle from a multi-dimensional perspective by taking the conceptual model of severe convective weather under a subtropical high. The conceptual model for this situation should be built by considering the three-dimensional structure of the subtropical high. In China, this situation can be divided into high-pitched (i.e., the higher the height, the greater the subtropical high range; Fig. 2a), low-slanted (i.e., the upper and lower layers are all controlled by subtropical high pressure; Fig. 2b), and fracture classes (i.e., the ridge of the western Pacific subtropical high will extend to the

west over the Chinese mainland during the summer; it sometimes splits into pieces over mainland China; Fig. 2c). It should be noted that these classifications are not mutually exclusive and each of these classifications could occur in different locations under the subtropical high on the same day. The classification of this conceptual model is based on the investigation of 40 days of short-duration heavy rain the days (56 days) when the western Pacific subtropical high controlled the Chinese mainland from June to August 2009. This example is not to present a scientific conclusion of a well-established conceptual model but to illustrate how to classify this case. For the conceptual model under the background of easterly wave, the height range of the easterly wave should be considered. For the linear severe convective weather associated with an upper-level level trough, the location of the weather and its relationship with the trough need to be determined. On the basis of the above analysis, the severe convective weather under the subtropical high is mainly influenced by the convergence or divergence of water vapor. It is also necessary to determine the degree of vulnerability by other surrounding systems under different structures of subtropical highs (e.g., see the discussion of a short-duration heavy rain event under a subtropical high by Liu 2011).

d. Multiscale fusion

From the forecast funnel perspective (Snellman 1982), the forecast process begins with the synoptic- (or larger-) scale and is downscaled to the mesoscale and local scale. Based on forecast funnel thinking, the forecast process could be initiated by synoptic-scale weather pattern type. However, it should be realized that in many instances of

FIG. 2. (a) Case of a high-pitched type (mesoscale analysis for the short-duration heavy rain under the subtropical high at 1200 UTC 19 Aug 2009). The blue shadowed area is the short-duration heavy rain area between 1200 and 1300 UTC. (b) Case of a low-slanted type focused on the area within line 316 [as in (a), but for 15 Aug 2009, from Fig. 2 of Liu (2011)]. (c) Case of a fracture type [as in (a), but for 12 Aug 2009, from Fig. 4 of Liu (2011)]. Solid lines marked 588, 316, 152, and 1010 indicate subtropical high margins at 500, 700, 850 hPa, and the ground, respectively.

severe convective weather, the synoptic-scale information at the top of the funnel may not be particularly useful in determining the meso- and microscale details of the convective event (Zhong and Chen 2017; Tian et al. 2018; Wu et al. 2018). In other words, the occurrence and development of severe convective weather are often affected by various scales in the forecasting process and the factors of various scales should be considered comprehensively. One should combine the most probable synoptic-scale, mesoscale, and microscale evolution in the conceptual model to produce the most common scenario.

e. Conceptual models need to be checked and corrected continuously

The establishment and development of conceptual models need to make use of historical cases, be based on an understanding of the weather mechanism, and then verified through operational applications. After the conceptual model is constructed, it is necessary to constantly check and modify it using new cases. This is especially true with the improvement of severe convective storm databases and the deepening of understanding of the severe convective weather process. Given the desire to update the conceptual model, is there an optimal number of cases needed? It is difficult to say how many cases of conceptual models need to be examined before they change and update. Severe convective weather mechanism analysis and conceptual model construction are similar to data statistics, but not completely consistent. When samples are used for statistical analysis, the sample size should meet the statistical requirements. In addition, more cases are more helpful for internal mechanism analysis. However, the small number of cases also can reveal the underlying principle, so as to build a conceptual model reflecting this internal causal relationship. It depends on whether the researchers can effectively discover the underlying mechanism in the limited case analysis and can this internal causality be tested repeatedly? If not, we need to increase the number in addition to the original number of cases. However, it seems difficult to determine the threshold or number.

5. Summary and conclusions

Conceptual models will still be useful for forecasters over the next decade or more, even with the development of objective algorithms, CAMs, and AI/machine learning. The conceptual model can help forecasters form forecast ideas quickly. It also can make up for the deficiencies of the numerical model and other objective methods. Furthermore, it can help forecasters understand the weather situation, and then let the forecasters

identify the key factors as soon as possible. Ultimately, conceptual models can help the forecaster serve the end users faster and better understand the forecast results during the service process.

Based on the above considerations, construction of new conceptual models should have the following characteristics: 1) be guided by purpose, 2) focus on improving the ability of forecasters, 3) have multiangle consideration, 4) have multiscale fusion, and 5) need to be tested and corrected continuously. The traditional conceptual models used for forecasts of severe convective weather should be updated to incorporate these principles. When constructing a conceptual model, it is important to consider what the conceptual model is built for, how to classify conceptual models, and how to build the conceptual model. According to the different uses of the conceptual model, the emphasis of the conceptual model should be different. These need to be taken into account when developing conceptual models of severe convective weather in China, as well as in other countries. Although, we have only discussed the situation in China, we hope that this paper can provide a reference for researchers of severe convective weather prediction in other countries when constructing conceptual models.

In closing, it is noted there are increasing numbers of ensemble and probabilistic forecasting products in the forecasting process. One question that must be considered in the future is how to make the conceptual model play a better role in the generation of subjective probability forecasting products. It is also important to optimize consistency from forecaster to forecaster so end users are not confused by frequently changing forecasts. These problems will take time to study and answer.

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