Sensitivity Analysis of Weather Research and Forecasting (WRF) Model Output Variables to The Thunderstorm Lifecycle and Its Application

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Abstract

Accurate and timely forecasts of thunderstorms at lead times of more than 6 hours can greatly improve the efficiency of the Air Traffic Flow Management (ATFM). To achieve this goal, the thunderstorms that occurred at Urumqi International Airport in 2020 are investigated using Weather Research and Forecasting (WRF) model output variables. An attempt has been made to study the sensitivities of some WRF output variables to the different stages (the cumulus, the mature, and the dissipating) of the thunderstorm lifecycle. The variables presented in this paper are wind speed (WSPD), composite radar reflectivity (CR), echo top (ET), convective available potential energy (CAPE), convective inhibition (CIN) and lift index (LI). It was found that CIN is most sensitive to an approaching thunderstorm. WSPD is extremely sensitive to thunderstorm occurrence, with CIN a close second. CAPE, CIN and LI are all sensitive to thunderstorm dissipating. To improve the thunderstorm forecasts, a simple and practical subjective thunderstorm forecasting method TSP (**T**hunder**s**torm **P**robability) based on the combination of above-mentioned variables, has been proposed. The comparison between objective TSP forecasts and manual subjective forecasts shows that TSP forecasts perform much better than manual forecasts in the summer period of 2020.

1 Introduction

The thunderstorm contains almost all of the weather hazards known to aviation, such as strong winds, lightning, turbulence, icing and so on, although not every thunderstorm contains all hazards. Thunderstorms as brief as a couple of hours can as a couple of hours can disrupt air traffic locally even nationwide because of strong disrupt air traffic locally even nationwide. They strongly reduced the efficiency of airport terminal area and en-route traffic flow in summer days and resulted in a significantly increasing number of flight delays, diversions or cancelations across China in recent years. Also in the USA, up to 90% of major flight delays could be attributed to thunderstorms during the summer months (Leighton 2006).

At present, ATFM responses to thunderstorms are always reactive as before (Mackeen et al. 1998): either increasing the distance between each aircraft, or diverting en route flights to other unaffected airports or holding the flights about to take off on the ground.

Flights to Urumqi Airport often take 2-6 h due to the long distance from other major cities. To ensure safe operations and efficient airspace use, ATFM at Urumqi Airport needs at least 2 h in advance to make tactical adjustments within the airport terminal area and 3-6 h for strategic maneuvering between transregional Flight Information Regions (FIRs) before thunderstorm occurrence.

There is growing demand for thunderstorm forecast in aviation industry in recent years. Accurate forecasts of the most likely areas where the thunderstorms will occur, how significant they might be, and when they will dissipate at lead times of more than 6 h can greatly improve the efficiency of the air traffic (Pinto 2007) and minimize additional costs for airlines and passengers.

So far, the most common methods for thunderstorm forecasting are nowcasting and numerical weather prediction (NWP). In aviation, Doppler weather radar, satellite, or lightning data are always applied to monitor the thunderstorm evolution and issue thunderstorm warnings. However, traditional nowcasting methods or algorithms are often based on weather radar observations, such as the TITAN system (Dixon and Wiener 1993) and the Storm-Cell Identification and Tracking (SCIT) algorithm (Johnson et al. 1998). Usually, these methods or algorithms have skill at predicting thunderstorm characteristics only in the 0-2 h time frame (Kober et al. 2012; Martin et al. 2016) and this skill rapidly declines owing to the difficulties of nowcasting storm initiation and evolution (Pinto 2007). The reason for that is that those methods or algorithms are spatio-temporal extrapolations relied on the assumption that the evolution of the detected convective system is primarily governed by advection. Unfortunately, issuing and disseminating thunderstorm warnings with lead times of less than 2 h offers little help for ATFM. Martin et al. (2016) developed an algorithm called Cb-LIKE (Cumulonimbus Likelihood) to provide thunderstorm forecast up to 6 h. Osinski and François (2018) constructed an ensemble for the very short forecast ranges between 1 and 6 h. But these two methods were solely for scientific purposes at the time.

Forecast guidance from NWP model is already operationally available today. At present, the production of aviation meteorological forecasts is based mainly on forecasters using NWP model data in combination with available observations. Furthermore, NWP model outperforms nowcasting methods after some lead time (Lin et al. 2005), especially when the convective system is strongly controlled by a synoptic-scale process (Yano et al. 2017), although in most cases the intrinsic uncertainty of NWP model and the stochastic nature of convection limit thunderstorm predictability in the first few hours of the integration (Kober et al. 2016).

Thus, a reliable high-resolution NWP model is an essential tool in predicting thunderstorms at long forecast lead times. It is important to evaluate and improve the skill of a model in predicting thunderstorm events. This paper aimed to fully exploit the potential of NWP model variables in thunderstorm forecasting in order to facilitate decision-making for ATFM at various stages of the thunderstorm.

The paper is organized as follows. In Sect. 2, the site description and the climatological aspects of thunderstorms at Urumqi Airport are presented. The thunderstorm cases considered, the NWP model, and its output variables used to study these cases are described in Sect. 3, including a brief description of the methodology adapted to the requirements of our study. Section 4 analyses the sensitivity of the WRF model variables to the different stages of the thunderstorm lifecycle and presents a simple and feasible thunderstorm forecasting method and its performance. Summary and conclusions are given in Sect. 5.

2 Study Area

Xinjiang Province is China's largest administrative region at the provincial level, with an area spanning over 1.6 million km², accounting for one-sixth of the country's territory. Furthermore, Xinjiang Air Traffic Management Bureau is in charge of the largest Flight Information Region (FIR) of China (i.e. Urumqi FIR),

covering an area of over 2.2 million km² (Fig. 1). Urumqi is the capital of the Xinjiang province. Urumqi International Airport (hereinafter Urumqi Airport) lies in a low-lying place surrounded by higher terrains in all directions, approximately 17 km northwest of the city center (Huang and Chen 2016).

During the past 30 years (1986-2015), a total of 166 thunderstorm days were recorded, with an average of fewer than 6 days each year. There was wide variability in the annual distribution of thunderstorm events with a maximum of 14 (in 2013) and a minimum of 0 (in 2001). More than 90% of thunderstorm days (152 out of 166) occurred from May through August. By month, thunderstorm events were most prevalent in June (48) and July (48), followed by August (30) and May (24), occasionally in September (9) and March (7), none in other months. Most thunderstorm events (95.2%) lasted less than 2 h. The climatological thunderstorm probability is highest during the evening (1400–1800 UTC; local time is UTC + 8 h) and lowest during the morning (0000–0400 UTC).

In statistical terms, thunderstorms are events with low probabilities at Urumqi Airport. Even so, an unexpected thunderstorm occurrence with the observations of thunder and/or lightning can cause air traffic chaos because there is only a single runway at Urumqi Airport and its capacity is close to the limit with the rapidly rising of the air traffic flow in recent years (Huang and Chen 2016).

For example, an unexpected thunderstorm hit Urumqi Airport on July 14, 2018, lasted about 3 h, disrupted air traffic, and resulted in 18 flights flying around in circles in limited airspace. From 1220 UTC, a thunder cloud was observed moving northeasterly and approaching Urumqi Airport (Fig. 3a). Some flights began to deviate from the original route to avoid the thunder cloud. In that day, all the flights could only fly in and out from the west side of the airport due to the unfavorable runway wind direction. At 1350 UTC, many places on the west side of the airport had been covered by thunder clouds. Flights had to negotiate the paths through the thunderstorm areas (Fig. 3b). After 1430 UTC, only a few flights took off along the different routes because the airspace over the airport was gradually covered by the thunderstorm (Fig. 3c). Around 1520 UTC, the thunderstorm blocked the airport, and all flights in and out had been suspended (Fig. 3d). The air traffic got back to normal after 1650 UTC when the thunderstorm dissipated. The thunderstorm event had not been foreseen earlier this day. Duty forecasters issued the thunderstorm warning after the lightning was reported by the air traffic controllers. ATFM blamed the chaos on forecasters afterward for not forecasting thunderstorms accurately in advance.

3 Data And Methodology

3.1 Data

The mesoscale model, WRF (ARW) (Skamarock et al. 2008), which has been adopted for operational usages at Urumqi Airport since 2015, has played a significant role in short- and medium-range weather forecasting (Huang and Zhang 2017). Unfortunately, only the data associated with the local WRF model in 2020 are preserved relatively intact because they are always discontinuous for some variables over the period of 2015 and 2020, due to poor maintenance, human errors, network problems, computer

shutdowns, unexpected power outages, or insufficient storage space, which limited the available sample of events. So we select the thunderstorm occurrences in 2020 for the study. It's not so bad that there are eleven thunderstorm events recorded at Urumqi Airport in 2020 (Table 1), ranking the second highest frequency of occurrence next to 2013 during the past 35 years.

Table 1
Thunderstorm events recorded at Urumqi Airport in 2020

Date	Time period	Phenomenon
05/13	1400-1600 UTC	Thunderstorm
05/23	1400-1530 UTC	Thunderstorm / Moderate wind
05/27	1400-1900 UTC	Thunderstorm / Light rain / Strong wind
06/05	1134-1200 UTC	Thunderstorm / Light rain / Moderate wind / Sandstorm
06/17	1630-1700 UTC	Thunderstorm
07/04	2135-2200 UTC	Thunderstorm / Light rain / Strong wind / Sand
07/16	1430 UTC	Thunderstorm (lightning visible, no thunder heard)
07/22	1417-1730 UTC	Thunderstorm / Moderate wind
08/03	1720 UTC	Thunderstorm (lightning visible, no thunder heard) / Light rain
08/04	1417-1630 UTC	Thunderstorm / Light rain / Strong wind
08/06	1517-1530 UTC	Thunderstorm

3.2 Model setup

As illustrated in Fig. 4, the model setup included a coarse 27 km domain (d01), and two nested domains: 9 km grid resolution (d02) and 3 km grid resolution (d03). All domains have model's own 35 sigma levels and a 50-hPa top. The time step is 90 s in the 27-km domain, 30 s in the 9-km, and 10 s in the 3-km domain. The initial atmospheric and lateral boundary conditions for all 3 domains, including soil moisture and temperature, are taken from the NCEP Global Forecast System (GFS) real-time forecasts at 6-h intervals, which are gridded to a horizontal resolution of $1^{\circ} \times 1^{\circ}$.

The model physics packages chosen on all three domains are the Rapid Radiative Transfer Model (RRTM) longwave radiation (Mlawer et al. 1997), the Dudhia shortwave radiation scheme (Dudhia 1989), the WRF single moment 3-class (WSM s) microphysics scheme (Hong et al. 2004), the YSU planetary boundary layer scheme (Hong et al. 2006) and the thermal diffusion land surface scheme. The Kain-Fritsch cumulus scheme (Kain 2004) is only used in the 27- and 9-km domains (Table 2), not in the 3-km domain.

At Urumqi Airport, the WRF model is run twice per day (initialized at 00 and 12 UTC, respectively, and run out to 60 h). Taking into account the model spinup and that these forecasts are available about 10 h after the initial forecast time, the first 12 h of the forecast are discarded. So the forecasts range from 12 h to 60 h. Six variables output from the innermost domain without the use of cumulus parametrization, are used to test their sensitivities to the different stages of the thunderstorm lifecycle. All model variables are processed at 15 min intervals, including AFWA (the US Air Force Weather Agency) diagnostic variables, which are available to the WRF model since WRF version 3.6 (Creighton et al. 2014).

Table 2
Overview of the WRF model configurations

Model aspects	Setting
Horizontal grid distance	27km / 9km / 3km
Integration time step	90 s / 30s / 10s
Model top	50 hpa
Microphysics	WSM3 scheme
Cumulus parameterization	Kain-Fritsch scheme(No Cumulus scheme in d03)
Longwave radiation	RRTM scheme
Shortwave radiation	Dudhia’s short wave radiation
Land surface layer	Thermal diffusion scheme
Planetary boundary layer	YSU scheme

3.3 Model output variables

The WRF output variables (or indices) selected as thunderstorm potential predictors for this study are displayed in Table 3. Most of these variables contain one or more of the ingredients that are necessary and sufficient for the development of a thunderstorm and they are widely used in thunderstorm detecting and forecasting (Galway 1956; Jorgensen et al. 1989; Parker 2002; Mukhopadhyay et al. 2003; Haklander and Delden 2003; Schmeits et al. 2005; Kunz 2007; Litta and Mohanty 2008; Gottlieb 2009; Wong et al. 2013; Zepka et al. 2014; Tse et al. 2014; Westermayer et al. 2016; Sarkar et al. 2019). Among these variables, WSPD is one of the criteria for defining severe thunderstorms (Rude 2011). The radar echo intensity (reflectivity) is often used for the detection of thunderstorm cells (Osinski 2018). Composite Reflectivity (CR) is composed of the greatest reflectivity from any elevation angle seen from the radar. CR can reveal the highest reflectivity in all echoes. CAPE represents vertically integrated positive buoyancy of an adiabatically rising parcel (Moncrieff and Miller 1976). CIN represents an energy well that must be surpassed by the parcel to realize its potential convective energy (Colby 1984). LI is a measure of thermal

stability of the atmosphere at 500 hPa (Means 1952). Hence, these six variables are selected for application in our study.

Table 3
List of the variables output from WRF model

Variable	Abbreviation	Description
WSPD10MAX	WSPD	Model wind speed
REED_COM	CR	Derived composite radar reflectivity
ECHOTOP	ET	Echo top height from Zetith
AFWA_CAPE	CAPE	The convective available potential energy
AFWA_CIN	CIN	The convective inhibition
AFWA_LIDX	LI	Surface-based lifted index

3.4 Methodology

The six variables fall into two groups. One is associated with higher values for a higher thunderstorm potential (e.g., CR) and the other with lower values with a higher thunderstorm potential (e.g., LI). We assume that thunderstorm probability increases monotonically with either increasing or decreasing variable values as Haklander (2003) did and divide the range of variables values exceeding some specified thresholds into four levels to specify the likelihood of thunderstorms, i.e. “low”, “moderate”, “high” and “very high” (Table 3), which is similar to fuzzy logic (Mueller et al. 2003; Hansen 2007; Keis (2015); Martin et al. 2016). The specified thresholds are based on operational experience referring to published values (e.g., Rasmussen and Wilhelmson 2003).

At Urumqi Airport, forecasters always use different colors (GREEN, YELLOW, ORANGE, and RED) to visualize the impact of weather on aviation to facilitate the perception of the information. GREEN stands for no impact, YELLOW for low impact, ORANGE for moderate impact and RED for high impact. Likewise, we visualize the potential of the thunderstorm occurrence with the same colors, according to the variable ranges as defined in Table 4, which can be interpreted as thunderstorm probabilities. Here GREEN, YELLOW, ORANGE and RED represent respectively “low” probability, “moderate” probability, “high” and “very high” probability.

Table 4 The value ranges of six variables and their corresponding color-coded probability of thunderstorm occurrence

Probability	Low	Moderate	High	Very high
WSPD (m s^{-1})	< 5	[5, 8)	[8,10)	≥ 10
CR (dBZ)	<30	[30,35)	[35, 40)	≥ 40
ET (km)	< 6	[6,8)	[8,10)	≥ 10
CAPE (J kg^{-1})	<100	[100, 200)	[200, 300)	≥ 300
CIN (J kg^{-1})	>200	(150, 200]	(100, 150]	≤ 100
LI ($^{\circ}\text{C}$)	< 0	(-1.0, 0]	[-1.0,2.0)	≤ -2.0

4 Results And Discussion

4.1 Sensitivity analysis

Generally, thunderstorm's lifecycle progresses through three stages: the cumulus, the mature, and the dissipating. We investigated the variable sensitivities to different stages of the thunderstorm lifecycle with time intervals of 3 h (see Fig. 5), including 0-3h before the thunderstorm (the cumulus stage), 0-3 h during the thunderstorm occurrence (the mature stage) and 0-3 h after the thunderstorm (the dissipating stage).

As we can see in Figure 5a, CIN is most sensitive to an approaching thunderstorm with six REDs and two ORANGEs of eleven 3-h time intervals. WSPD (two REDs), CR (two REDs), LI (one RED and four ORANGEs), TOP (one RED and three ORANGEs), and CAPE (one ORANGE) show "high" or "very high" probability in some cases before the thunderstorm.

WSPD is extremely sensitive to thunderstorm occurrences with four REDs and four ORANGEs, as well as seven YELLOWs of eighteen 3-h time intervals. CIN is second to WSPD with four REDs, two ORANGEs, and two YELLOWs. TOP and CR perform at comparable levels, followed by LI and CAPE (Fig. 5b).

At the thunderstorm dissipating stage, CAPE, CIN and LI all indicate "low" probability in all cases (Fig. 5c). It means that they are good predictors for thunderstorm dissipating.

In brief, CIN is the most sensitive variable before the thunderstorm, followed by WSPD, CR, LI, TOP, and CAPE. WSPD is extremely sensitive to thunderstorm occurrence, with CIN a close second. CAPE, CIN and LI are all sensitive to the dissipating of the thunderstorm. In most cases, CIN is sensitive to the whole thunderstorm lifecycle.

4.2 TSP method and its performance

To improve the thunderstorm forecasts and meet the needs of the aviation users, a simple and feasible thunderstorm forecasting method TSP (**T**hunder**s**torm **P**robability) based on the combination of these variables has been proposed. Our focus is on the occurrence of site-specific thunderstorms, not the timing of thunderstorms. The method is made up of three main steps: variables monitoring, probability assessing and decision making.

Specifically, these variables related to thunderstorm potential are routinely monitored every twelve hours. Once half or more of these variables show "moderate" probability (YELLOW) or higher in the same 3-h intervals, it is time to consider whether to issue forecasts and warnings. Issuing forecasts and warnings

immediately without thinking about the synoptic conditions, so long as half or more of these variables including CIN and WSPD show “high” or “very high” probability (ORANGE or RED).

Then we compared TSP forecasts with the manual forecasts at Urumqi Airport using the thunderstorm observations in the summer period of 2020.

Weather forecasts of Urumqi Airport are provided by aviation forecasters as terminal aerodrome forecasts (TAFs) in an alphanumeric coded form according to regulations from the International Civil Aviation Organization (ICAO 1998) and the World Meteorological Organization (WMO 1998). TAFs contain detailed forecast information on wind, visibility, cloud amount, cloud-base height, and weather phenomenon in the vicinity of the airport. TAFs are issued 12 times a day at Urumqi Airport with 8 short TAFs (valid for up to the next 9 h) and 4 long TAFs (valid for up to the next 24 h), updating every 3 and 6 hours, respectively. TAFs must be quickly amended (TAF AMD) whenever observed conditions differ significantly from forecast conditions. Airport observations are provided by aviation observers as “meteorological aviation routine weather reports” (METARs) every half hour and “additional special observations” (SPECIs) whenever conditions change significantly.

At Urumqi Airport, a thunderstorm observation is defined as a situation where thunder is heard or lightning is visible. It usually implies that a lightning discharge has occurred within a radius of about 20 km around the observer (Haklander and Delden 2003). But for the events with only lightning visible and no thunder heard, the distance between the observer and the thunderstorm is uncertain, and the distance is much more uncertain when lightning is visible during nighttime at much greater distances. For example, the distance between the observer and the lightning was about 30 km on July 16 and 50 km on August 3, respectively, according to the radar observations and the lightning data. The forecasters and the observers have big debates on whether these kinds of cases should be recorded as thunderstorm events. To be consistent with the international agreement in defining a thunderstorm day (Reap 1993; Bosart 1994; Haklander and Delden 2003), we have excluded these two cases from the list of the comparison table (Table 5).

Table 5

The comparison between TSP forecasts and TAFs relating to thunderstorm occurrence at Urumqi Airport in the summer period of 2020

Date	Time Period	Initial forecast time	TSP forecast	Leadtime	TAF	TAF AMD time
05/13	1400-1600 UTC	05/12/1200UTC	YES	12 h +	NO	-
05/23	1400-1530 UTC	05/21/1200UTC	YES	36 h +	NO	-
05/27	1400-1900 UTC	05/25/1200UTC	YES	36 h +	YES	-
06/05	1134-1200 UTC	06/03/1200UTC	YES	24 h +	YES	-
06/17	1630-1700 UTC	06/16/0000UTC	NO	-	NO	06/17/1648UTC
07/04	2135-2200 UTC	07/04/0000UTC	NO	-	NO	07/05/2140UTC
07/22	1417-1730 UTC	07/21/0000UTC	YES	24 h +	NO	07/22/1504UTC
08/04	1417-1630 UTC	08/03/1200UTC	YES	12 h +	NO	08/04/1438UTC
08/06	1517-1530 UTC	08/06/0000UTC	NO	-	NO	-

The comparison shows that TSP method captured six of nine events with lead time more than 12 h and even up to more than 36 h in some cases, while manual TAFs hit only two with lead time more than 12 h (Table 5). More importantly, the TSP method captured all five events lasting more than 1 h, which have high impacts on air traffic flow.

In order to better assess the performance of TSP method, the following 4 skill scores based on the 2×2 contingency table (Table 6) were evaluated: probability of detection (POD), critical success index (CSI), false alarm ratio (FAR) and missing rate (MR). A perfect forecast would have skill scores of POD = 1, CSI = 1, MR = 0, and FAR = 0 (Wilks 1995). Those skill scores related to d in Table 6, such as hit rate (HR) and Heidke skill score (HSS) (Umakanth et al. 2020), are not discussed in this paper because non thunderstorm events (events without thunderstorm) are 10 or more times than thunderstorm events at Urumqi Airport during the warm season, and they were forecast much better than thunderstorm events by both TSP and TAFs.

Table 6
2×2 contingency table of
thunderstorm observations
and forecasts

Forecast	Observation	
	Yes	No
Yes	<i>a</i>	<i>b</i>
No	<i>c</i>	<i>d</i>

As we can see from Table 7, that the POD of TSP is promising with a value of 0.67, while that of TAFs is only 0.22. The CSI of TSP also yields better score than that of TAFs. The FAR value is 0.40 for TSP and 0.67 for TAFs. Usually, the performance is considered acceptable when the $FAR \leq 0.5$ (De Perez et al. 2015) and it helps decision makers increase their confidence in responding to thunderstorm events. On the contrary, decision makers would hesitate to take response measure because of the high FAR score (> 0.5).

Furthermore, the MR value is only 0.33 for TSP but 0.78 for TAFs. It means that forecasters missed nearly 80% of the thunderstorm events. In addition, they amended the TAFs only after thunderstorms had already occurred in four of seven missed events. For the other three missed events, duty forecasters didn't even amend the TAFs for unknown reasons. It can be inferred from the TAFs that they always underestimated the possibility of thunderstorm events, or they preferred to be careful to avoid false alarms rather than to be audacious to avoid misses. In practice, the high MR score is harder to accept than the high FAR score because decision makers or aviation users are always completely unprepared for the unexpected events.

Table 7
The skill scores' definition and their values for TSP and TAFs
during 2020 warm season

Skill scores	Definition	TSP	TAFs
Probability of detection	$POD = a/(a+c)$	0.67	0.22
Critical success index	$CSI = a/(a+b+c)$	0.46	0.15
False alarm rate	$FAR = b/(a+b)$	0.40	0.67
Missing rate	$MR = c/(a+c)$	0.33	0.78

4.3 Discussion

Scientific weather forecasting on a daily basis first became feasible during the end of the nineteenth century (Schaefer and Joseph 1986). For over a hundred years, many methods have been implemented in thunderstorm forecasting. But none of these methods was sufficient to identify its prior to others (Chauduri et al. 2013).

Some methods or techniques developed in recent years are displayed in Table 8. Among them, Rajeevan et al (2012) developed a statistical model based on Binary Logistic Regression (BLR) technique to predict the probability of thunderstorm (lightning) over the SHAR region, at the request of the SHAR Space Centre of at least 1–24 hours in advance. They selected six WRF model predictors from a pool of 61 potential predictors. Their method showed a POD of 0.69, a CSI of 0.54 and a FAR of 0.29. The Hong Kong Observatory has enhanced its radar-based nowcasting system SWIRLS to SWIRLS-II with an extrapolation-model-blending approach to predict severe weather associated with intense thunderstorms (Li et al. 2014). The POD and CSI of SWIRLS-II decreased from 0.8 and 0.5 to 0.3 and 0.1 with the lead time increasing from 1 h to 6 h. Gubenko and Rubinshtein (2015) proposed a new index $//w$ for the thunderstorm forecasting that takes account of the vertical component of wind speed. The POD and FAR values of $//w$ are 0.42 and 0.52, 0.34 and 0.31, respectively, for the verification based on station data and for the verification based on “station + WWLLN (World Wide Lightning Location Network)” data. Martin et al (2016) developed an algorithm called Cb-LIKE (**C**umulonimbus **L**ikelihood) with the fuzzy logic to provide thunderstorm forecast up to six hours ahead. The POD and CSI of Cb-LIKE increased from 0.34 and 0.19 to 0.44 and 0.28, while the FAR decreased from 0.70 to 0.58 when the neighbourhood size increased from 2.8 km to 19.6 km. Umakanth et al (2020) attempted the prediction of thunderstorms using artificial neural network (ANN) and auto-regressive moving average (ARMA) techniques and assessed the skill of ARMA and ANN techniques for total totals index (TTI) parameter in forecasting the thunderstorm occurrence at two stations. The values of POD, CSI and FAR for ARMA and ANN with a training percentage of 70% are 0.62-0.63 and 0.73-0.87, 0.32-0.36 and 0.60-0.78, and 0.53-0.60 and 0.11-0.22, respectively.

Table 8
Summary of some methods or techniques developed in recent years

Literature	Method	POD	CSI	FAR	Lead Time
Rajeevan et al (2012)	BLR	0.69	0.54	0.29	1-24 h
Li et al (2014)	SWIRLS-II	0.30-0.80	0.10-0.50	—	1-6 h
Gubenko and Rubinshtein(2015)	$//w$	0.42-0.52	—	0.31-0.34	—
Martin et al (2016)	Cb-link	0.34-0.44	0.19-0.28	0.58-0.70	0-6 h
Umakanth et al (2020)	ARMA	0.62-0.63	0.32-0.36	0.53-0.60	—
	ANN	0.73-0.87	0.60-0.78	0.11-0.22	—
— Data is not available					

From skill scores analysis, BLR (Rajeevan et al. 2012) and ANN (Umakanth et al. 2020) have better performance than TSP with higher PODs and CSIs, and lower FARs. However, BLR has no obvious advantages over TSP in lead time, which is very important for ATFM. As for ANN, the researchers first decoded NCEP (National Centers for Environmental Prediction) reanalysis data with MATLAB software, calculated nine thunderstorm-related parameters, selected six input parameters as inputs to predict TTI as output, and then experimented in three training sets, i.e., 90%, 80% and 70%, in order to know the output prediction for the remaining 10%, 20% and 30%. Compared with TSP, ANN is a little complicated and its lead time is unknown.

5 Summary And Conclusions

Current thunderstorm forecasts at Urumqi Airport cannot satisfy the aviation users' need—accurate and timely forecasts at lead times of more than 6 hours. In view of the importance and impact of thunderstorms on ATFM and other aviation users, a sensitivity analysis of WRF model output variables to the different stages of the thunderstorm lifecycle had been undertaken at Urumqi Airport.

Six WRF model output variables, including variables output from AFWA module embedded in WRF model, WSPD, CR, ET, CAPE, CIN and LI are selected to do sensitivity analysis. As expected, these variables have different sensitivities to the different stages of the thunderstorm lifecycle. Among them, CIN is most sensitive to an approaching thunderstorm, WSPD is extremely sensitive to thunderstorm occurrence, and CAPE, CIN and LI are all sensitive to thunderstorm dissipating.

Based on the combination of these variables, we presented a simple and feasible objective thunderstorm forecasting method TSP and compared it with the subjective TAFs issued by aviation forecasters at Urumqi Airport. The results show that TSP forecasts perform much better than TAFs in the summer period of 2020. Compared with other methods or techniques developed in recent years, TSP method is more simple and practice.

The conclusions obtained in this paper were based on site-specific events, so we are not sure whether the findings of this study are equally valid in other regions. It is also possible that other variables, which we have not studied, contain information on the probability of a thunderstorm. In addition, the output variables and the large scale synoptic features associated with the thunderstorm occurrence also depend on the physical parameterization schemes used in WRF model, especially the convective parameterization schemes. And more modelling studies are required to better understand the physical mechanisms of thunderstorm lifecycle.

Declarations

Conflict of interest The authors declare that they have no known competing interests for this publication.

Authors' contributions Haibo Huang contributed to methodology, analysis, writing, reviewing and editing. Caiyan Lin contributed to analysis, reviewing and editing. Yangquan Chen contributed to data preparation

and model simulations.

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Figures

Figure 1

Map of China Flight Information Regions (FIRs).

Figure 2

The duration of the thunderstorm at Urumqi Airport.

Figure 3

Schematic map of the impact of the thunderstorm on Urumqi Airport occurred on July 14, 2018, which is provided by ATFM. **a** 1220 UTC, **b** 1350 UTC, **c** 1430 UTC and **d** 1520 UTC (The dark shaded polygonal area is the terminal area of Urumqi Airport)

Figure 4

The WRF model domains.

Figure 5

The variable sensitivities to different stages of the thunderstorm lifecycle. **a** the cumulus stage, **b** the mature stage, **c** the dissipating stage