Estimation of TAMDAR Observational Error

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1 Introduction

Automated aircraft observations from different communication systems, which have been increasing significantly over the past few years, are becoming an important part in the global observing system. Operational numerical prediction centers have begun to ingest automated aircraft reports from AirCraft Addressing and Reporting System (ACARS) as a part of Aircraft Meteorological Data Reports (AMDAR) program of the World Meteorological Organization (WMO) into regional and global data assimilation systems (Schwartz et al. 1995; Drue et al. 2008). National Meteorogical Center in the United States have reported improved forecasts by using aircraft data (DiMego et al. 1992), and Smith and Benjamin (1994) showed that ACARS reports improved short-range forecasts of upper-level winds and temperatures when added to wind profiler data over the central United States. However, the complete absence of humidity observations and high curise height (mostly above 20,000ft) are two shortfalls of the current aircraft observation set(Moninger et al. 2009). As we know, most of the moisture and convective activity are below the altitudes of tropopause (about 25000 feet). Other than scattered rawinsonde, there are no other in situ observations, especially humidity routinely collected in this region of the atmosphere(Daniels et al. 2006). To make up for the existing technologies, a low-cost sensor called TAMDAR is developed by AirDat, LLC under the sponsorship of NASA's TAMDAR project as part of Aviation Safety and Security Program, according to requirements defined by NASA, NOAA/FSL, and WMO (http://www.airdat.com).

AirDat's TAMDAR system has been providing a continuous stream of real time observations in continuous operation on regional airliners since December 2004. Aircrafts under contract for TAMDAR provide coverage of the continental United States and Alaska, including locations and times not available from any other observing system. TAMDAR measures thousands of high-frequency daily observations of humidity, icing, and turbulence besides conventional temperature, pressure and winds aloft with GPS time/date/position/attitude in near real time, which largely are below altitudes of 25000 feet. Considering the advantages, TAMDAR measurements are becoming a major source of input data in data assimilation system for the improvement of mesoscale numerical weather forecasts and the overall safety of aviation in the future. However, we need to master the error information of measurements as a new input source. Also, the estimation of observation error is necessary for providing initial conditions for numerical weather forecasts, since they provide a basis for weighting information among different types of observations and a forecast background in data assimilation system to obtain a statistically optimal estimated values of true values (Benjamin et al. 1999).

Some methods used for evaluating observational error have been addressed by previous investigations. Generally, observational error include measurement error, reporting error (also considered as measurement error herein) and representativeness error (meso-scale variability) (Daley 1991; Schwartz 1995). Richner and Phillips,1981 used three ascents with two sondes on the same balloon to take simultaneously measurements of the same volume of air, which showed the deviations between two sondes lied well within the accuracies specified by the manufacturers. Obviously, the method gave measurement error. As we mentioned, this is not the only source of error. Whenever we wish to compare two observations or observation and forecast (assimilation), representativeness error must be taken into account.

Sullivan, et al, 1993 updated temperature error statistics for NOAA-10 when the retrieval system in National Meteorological Center (NMC) changed from 'statistial' to 'physical'. In this study radiosonde was considered as the reference value (true value), and the loose match condition, 4-h (time seperation) and 330km (distance) between radiosonde and satellite data, is used. The research introduced rawinsonde observational error and large representativeness error.

With the appearance and increasing of aircraft observation as a new input to initial condition for numerical weather forecast, the quality of aircraft observation has been subject to some studies. Schwartz and Benjamin,1995 gave the difference between rawinsonde and ACARS around Denver airport as a function of time and distance separation. A standard deviation of 0.97°C in temperature was reduced to 0.59°C through using the stricter match condition from 150km and 90min to 25km and 15min due to the representativeness error decreasing. The study provided an upper bound on combined error of ACARS and rawinsonde data and representativeness error. Also, they found the direction difference is highly correlated with lighter wind speeds, and the large direction differences at low wind speed is related to mesoscale variability, especially from turbulence in the boundary layer.

As a further study to obtain the independent observation error of ACARS, Benjamin and Schwartz,1999 reported on a collocation study of ACARS reports with different tail numbers to estimate observation error, assuming the equivalent expected error from each aircraft and the minimization of representativeness error by strict match conditon with 1.25km and 2min and no reported vertical separation. They gave the temperature rms error of 0.69-1.09 °C and wind vector error of 1.6-2.5 m/s in vertical distribution which are comparable to rawinsonde. The method and assumptions are both reasonable, but it's a challenge for TAMDAR to get enough data for statistics in so strict match condition. Lately, Moninger and Benjamin 2009 gives the error characteristics of TAMDAR by comparing to RUC 1hr-forecast with the resolution of 20km. (not considering RUC 1-h forecast to be "truth",rather forcing some independence from any particular observation type). The results show the difference of 1°C, 8%-20%, and 3-5m/s in temperature, relative humidity, and wind observations respectively. Beyond question, the difference includes TAMDAR observations error, representativeness error, and RUC 1-h forecast error.

Two questions can be found in past research for understanding the quality of TAMDAR: 1. United observational error sources are included in error statistics. 2. Wind error is calculated as a whole. Carroll and Eyre, 2007 developed a statistics method to calculate the standard deviation of observation error of each observation type by three different observation types under a assumption that observational error of different observation systems is uncorrelated, which is usually reasonable in error theory. In this study, this method will be applied to estimate TAMDAR observation error. As we mentioned, the wind speed and direction error changing with wind speed significantly is a characteristics of wind observation. So, much to be desired is to estimate wind speed and direction error by wind speed.

Worth speaking, the representativeness error exist all the time, even if the strict match condition is used, like Benjamin and Schwartz,1999. But we will minimize it with strict match condition as far as possible in our study.

2 Methodologies and Dataset

2.1 Error analysis for three-way collocation statistics

The observation x_o of variable x, can be expressed as

$$x_o = x_t + x_b + x_\varepsilon \qquad (1)$$

Where x_t is the true value of variable x, x_b is the bias (mean error) and x_ε is the random error (which, by definition, has zero mean).

For a set of three collocated observation types i, j, and k, we can obtain the following corresponding set of equations:

$$x_o^i = x_t + x_b^i + x_\varepsilon^i , \qquad (2)$$

$$x_o^j = x_t + x_b^j + x_\varepsilon^j , \qquad (3)$$

$$x_o^k = x_t + x_b^k + x_\varepsilon^k . \qquad (4)$$

The difference between observation types i and j is given by

$$x_o^i - x_o^j = x_b^i - x_b^j + x_\varepsilon^i - x_\varepsilon^j \qquad (5)$$

For a set of observations, the mean difference between observation types i and j is

$$b_{ij} = \overline{x_o^i} - \overline{x_o^j} = \overline{x_b^i} - \overline{x_b^j} \qquad (6)$$

and the variance of the difference between two observation types is

$$V_{ij} = [(x_o^i - x_o^j) - b_{ij}]^2 = (\overline{x_\varepsilon^i} - \overline{x_\varepsilon^j})^2 = (\overline{x_\varepsilon^i})^2 + (\overline{x_\varepsilon^j})^2 - 2\overline{x_\varepsilon^i x_\varepsilon^j} . \qquad (7)$$

Therefore, $V_{ij} = \sigma_i^2 + \sigma_j^2 - 2 r_{ij} \sigma_i \sigma_j \qquad (8)$

where σ_i^2 is the variance of error in observation type i, and r_{ij} is the correlation of error between types i and j.

In like manner, the following two sets of observation pairs can be obtained:

$$V_{jk} = \sigma_j^2 + \sigma_k^2 - 2 r_{jk} \sigma_j \sigma_k \qquad (9)$$

$$V_{ki} = \sigma_k^2 + \sigma_i^2 - 2 r_{ki} \sigma_k \sigma_i \qquad (10)$$

The simultaneous Eqs.(8)-(10) can be solved to give the variance of error in each observation type as follows:

$$\sigma_i^2 = \frac{1}{2}(V_{ij} + V_{ki} - V_{jk}) + (r_{ij}\sigma_i\sigma_j + r_{jk}\sigma_j\sigma_k - r_{ki}\sigma_k\sigma_i) \qquad (11)$$

It is usually reasonable to assume that the errors in measurements made by totally independent techniques will be truly independent. So, $r = 0$.

Then, Eq. (A11) becomes $\sigma_i^2 = \frac{1}{2}(V_{ij} + V_{ki} - V_{jk})$ (12)

Eq. (12) allows us to estimate the error variance of each observation type from the difference statistics of observations.

The set of simultaneous equation from Carroll (2007) firstly was used to estimate the error variances for satellite data.

In this paper, we also suppose that the short-term forecast error of a non-linear numerical model is uncorrelated to the error of any observation system.

2.2 Dateset

In this study, rawinsonde, TAMDAR and WRF 6-h forecast as three data sources are used to estimate TAMDAR observational error.

Rawinsonde

Rawinsonde from NCAR archived observation data files, routinely transmitted over Global Telecommunication System (GTS), were used. Rawinsonde in this study cover observations twice daily at 0000 and 1200 UTC in continent United States. Time and space difference between rawinsonde and TAMDAR was determined using this exact position data at each level.

TAMDAR

TAMDAR observations are made at 10 hPa pressure intervals up to 200 hPa above ground level with the largest interval of 3 minutes during ascent and descent. As they are made, observations are transmitted to AirDat's data center and are typically available for model assimilation or analysis within a minute of the time of observation. NOAA ESRL Global Systems Division (GSD) is playing a central role in the distribution and evaluation and initial quality control (reports formatting or units error) of TAMDAR data. In this study, TAMDAR observations are collected via the MADIS dataset of AirDat, LLC based on MADIS program from NOAA GSD. A basic quality control procedure is performed on the raw TAMDAR data, including vertical consistency check (super adiabatic check and wind shear check) and dry convective adjustment. TAMDAR observations cover most of main airports in the east-middle and northwest of CONUS (figure 1). The dataset in this study uses a winter month (January) and a summer month (1-25 in June) in 2010. The time serial of the number of TAMDAR measurements is displayed in figure 2.

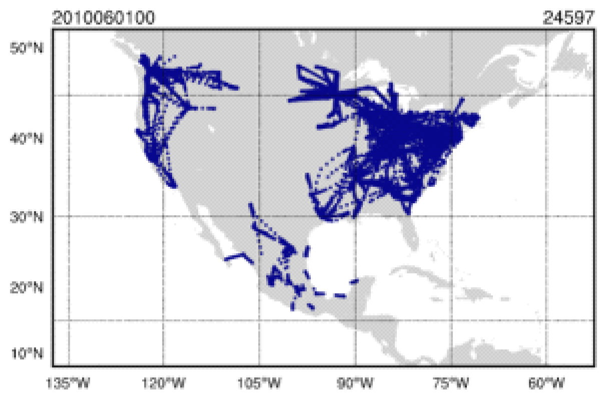

Fig.1 The distribution and number of TAMDAR observations on June 1, 2010

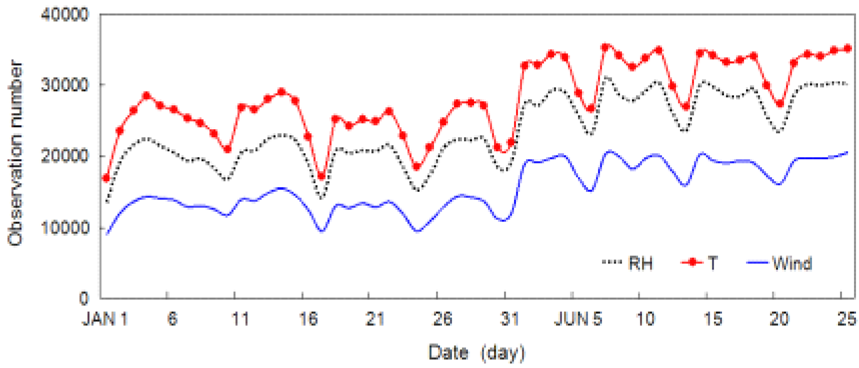

Fig.2 The number of RH, T, wind measurements in TAMDAR observations

In general, the amount of TAMDAR measurements available decreases with altitude. For assuring statistics meaning and decreasing the effect of meso-scale perturbation, different matchup conditions are applied in three levels for getting enough data pairs. Data pairs were created for every TAMDAR report that occurred within certain space (longitude/latitude) and time interval of rawinsonde reports. It means that one observation represents the mean value of a small volume of air within certain space and time range. The match condition is given in table 1.

Table 1 Matchup conditions between rawinsonde and TAMDAR

>775hPa	775-450hPa	<450hPa
10km, 1hour	20km, 1hour	30km, 1hour

A total of 23551 matched rawinsonde/TAMDAR data pairs were found meeting the time and distance separation constraints. Although cruder match condition is in the upper level, the pairs number mainly concentrate on strict condition. Figure 3 depicts the distribution of these pairs by distance and time separation. Approximately 70%,71%,61% of the data pairs of temperature, RH and wind were separated less than 10km, and the distribution by time separation shows that data pairs have some distinct peaks of TAMDAR reports 0-60 min after rawinsonde report time, which is a result of the intersection of United Airlines flight schedule.

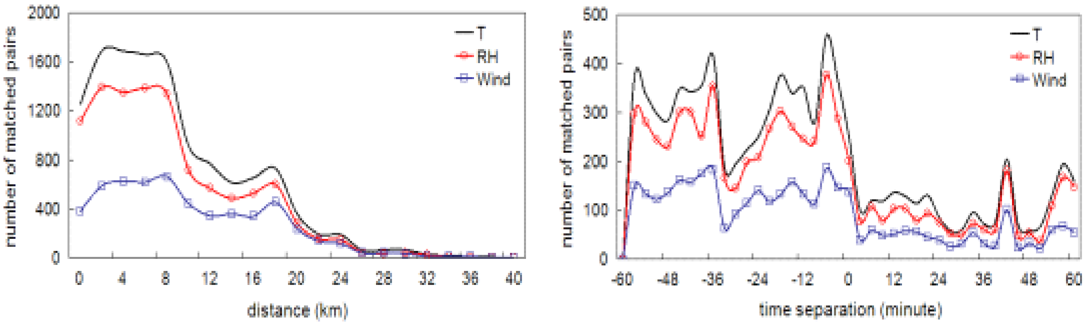

Fig.3 The distribution of pairs by distance and time separation

WRF forecast

WRF 6-h forecast with the resolution of 20km is used as the third data source. The initial condition and boundry condition both derive from GFS. The vertical levels consist of 35 eta-layer with the model top at 50 hPa. All the physics process are basic and conventional in table 2.

The difference between WRF 6h forecast and observation is obtained by interpolating four grid points of forecast to observation location.

Table 2 The physics processes applied in WRF 6-h forecast

micro-physics	longwave radiation	shortwave radiation	surface-layer	land-surface	boundary-layer	cumulus
Kessler	RRTM	Goddard short wave	Monin-Obukhov	Unified Noah land-surface	YSU	Kain-Fritsch

3. Error estimation analysis

According to the formula (12), the standard deviation of TAMDAR observation error can be expressed as $\sigma_T^2 = \frac{1}{2}(V_{S-F} + V_{T-F} + V_{S-F})$

where T,S,F means TAMDAR,rawinsonde,WRF 6-h forecast respectively; σ means the standard deviation of TAMDAR. V means the variance of the difference between two observation types.

3.1 Difference distribution

Figure 4/5 shows the like-gauss distribution pattern of the difference between TAMDAR and rawinsonde/WRF 6h forecast and gaussian function distribution according to mean and standard deviation of the differences. The difference between two types can be affected by meso-scale perturbation, which will lead to abnormal values, so we reject the observation pairs with difference more than 40%, 10m/s and 60° in variable RH, speed and direction. We can see that T and speed difference basically meet gauss distribution function, but RH and direction concentrate more pairs near 0.

Table 3 depicts the statistics, including bias(B), variances(σ) and the area percent of 1/1.64/ 2.58-σ. The area percent of 1/1.64/ 2.58- σ of standard gaussian function is 68.3/90/99%.

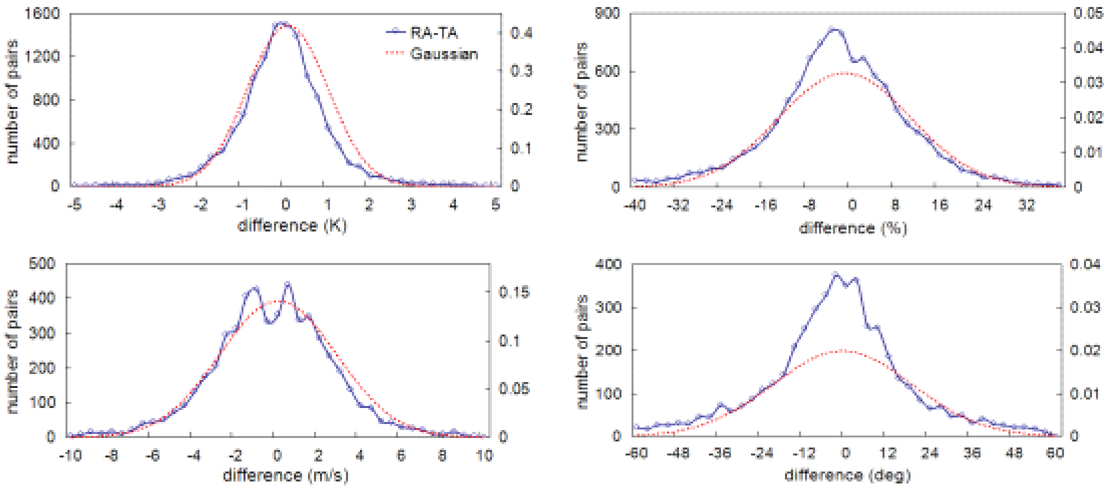

Fig.4 The difference of variable T, RH, speed, direction between TAMDAR and rawinsonde. The dotted line is gaussian distribution according to mean and standard deviation of the difference.

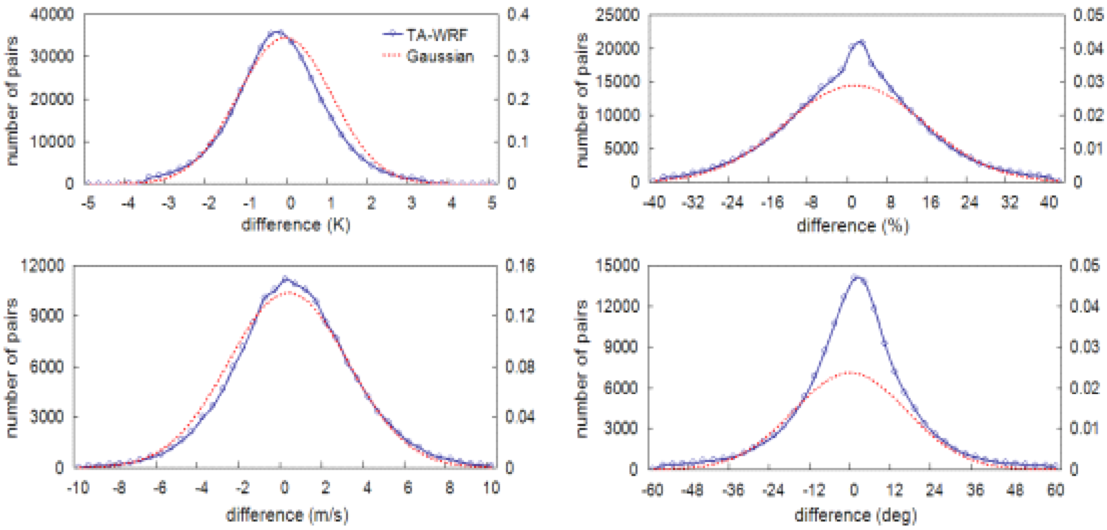

Fig.5 The difference of variable T, RH, speed, direction between TAMDAR and WRF 6h forecast

Table 3 The statistics of the differences between TAMDAR and rawinsonde/WRF 6h forecast

		RH	T	Speed	Direction
Rawinsonde -TAMDAR	N	9994	12549	5384	4810
	B	-1.57 (%)	0.04 (°C)	-0.004 (m/s)	-1.22 (°)
	σ	12.18 (%)	1.06 (°C)	2.83 (m/s)	20.13 (°)
	1-σ	72.1%	74.9%	71.5%	73.6%
	1.64-σ	89.3%	90.7%	89.8%	87.7%
	2.58-σ	97.8%	97.5%	97.5%	97.8%
TAMDAR -forecast	N	284586	374198	149044	143572
	B	-0.37 (%)	-0.16 (°C)	0.15 (m/s)	-1.39 (°)
	σ	13.81 (%)	1.16 (°C)	2.88 (m/s)	16.83 (°)
	1-σ	69.8%	70.1%	70.1%	74.3%
	1.64-σ	88.8%	89.1%	89.6%	89.5%
	2.58-σ	98.3%	98.3%	98.5%	97.1%

It can be seen that the bias of variable RH, T, speed between TAMDAR and rawinsonde is only O~10^{-2} -10^{-3}, which shows the quality of TAMDAR as a whole is comparable to rawinsonde and creditable with few abnormal measurements, and the area percent of **1-**σ of the differences are both more than 68.3%, which means more data pairs have comparable quality. Also we can get the conclusion that the both differences is near gauss distribution at 1.64-σ. However, the meso-scale perturbation still leads to some abnormal observations from the area percent of 2.58-σ. The data pairs with large difference, which maybe derive from the rough match condition (meso-scale perturebation) or occasional observations with bad quality, are few so as not to significantly affect the error estimation of observation itself. It's deserved to mention that the variables RH, speed and direction should be paid close attention to. The total σ of RH should be larger than that in lower and meaningful levels because the error in the upper levels (above 400 hPa) will increase remarkably where there is only few water vapor. Homoplastically, the error of direction seems more than the reasonable range. Actually, as a characteristic of wind observation, the direction error is related to the wind speed. Beyond question, there is more chance to get bad quality observations with larger direction error in the observations with smaller speed due to mesoscale variability and accurate heading information and frequent mancuvers(Moninger et al. 2009).

3.2 Vertical distribution of error

The statistics error (standard deviation) of variables T, RH, speed and direction of TAMDAR are presented in figure 6-9.

We can see from figure 6 that the temperature error for TAMDAR is 0.6~0.95°C, smaller than rawinsonde in winter month. The extreme difference of about 0.15°C in 500hPa in summer month and in 700hPa in winter month, which maybe is related to the higher mesoscale perturbation level in sunmmer month, shows the good quality of TAMDAR measurements. Moninger et al, 2009 gives about 1K difference between TAMDAR and RUC 1-h forecast, which is larger than our study partly because the difference included RUC forecast error.

The abundant relative humidity observations of TAMDAR provide a complement to other observation types, which will play an very important role to the numerical weather (convective) forecast. RH error is much smaller for TAMDAR than for rawinsonde in summer month, up to 3% in 500hPa, and the errors are similar in winter month. The estimated error range is agreeable with a reporting error of 5%-10% from Daniels (NASA Langley Research Center, 2002). RH observations of TAMDAR with good quality will make up the few rawinsonde observation fully.

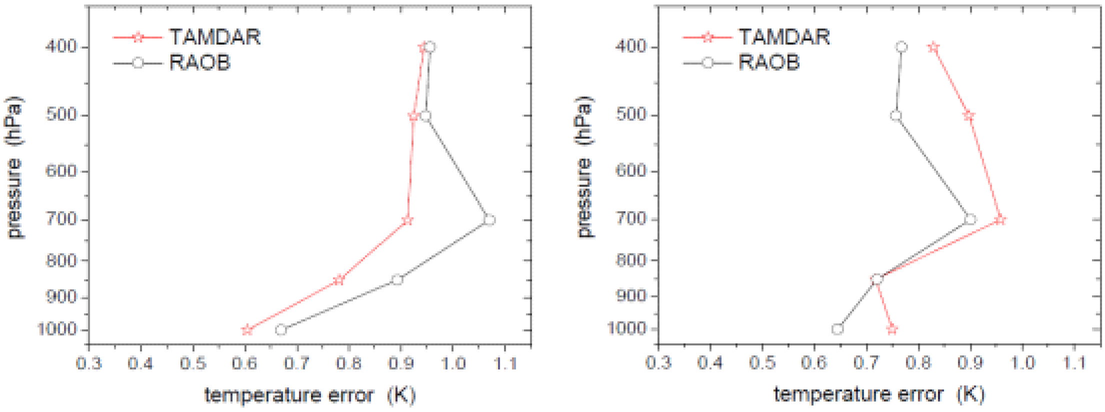

Figure 6 The standard deviation of error of T of TAMDAR in January and June

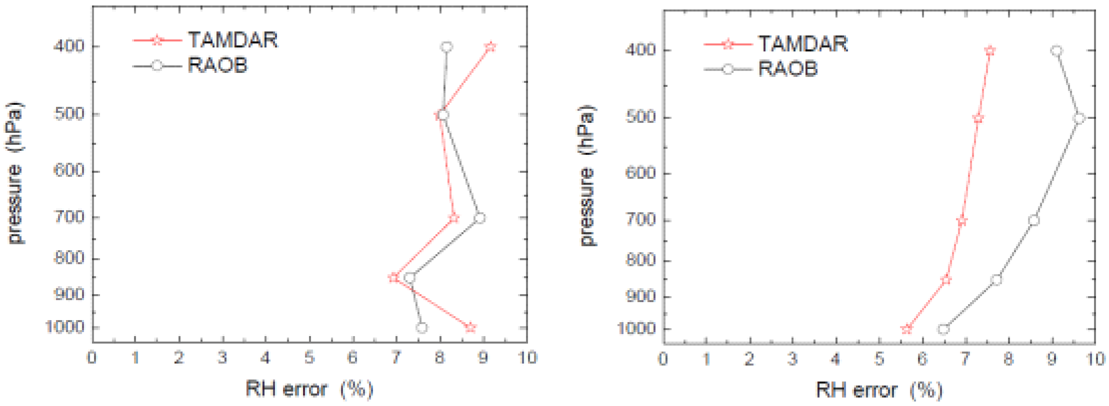

Figure 7 The same as Fig.6, but RH

From the statistics of wind observations (figure 8,9), the speed observation of TAMDAR is inferior to that of rawinsonde, and the largest difference is up to 1.25m/s at 700hPa level in summer month. The direction errors of rawinsonde and TAMDAR are both large in lower levels, especially in summer month where the small scale perturbation is strong in underlying surface.

Actually, the wind (speed, direction) observations of TAMDAR are obtained with inputs from an external GPS and external Heading and Acceleration/Attitude Module. The less accurate heading information provided to TAMDAR, which mayber affected by manipulation, will be responsible for the lower quality wind obervation, especially to wind observations with small speed.

As we mentioned above, it's reasonable to estimate wind speed and direction error by wind speed. Figure 10 presents speed errors and direction errors of TAMDAR and rawinsonde by wind speed. Generally, wind (direction) speed error increase (decrease) with speed. In accord with mentioned above, the speed observation of TAMDAR is inferior to rawinsonde. However, to be encouraging, the error of TAMDAR wind observations with speed more than 15m/s is smaller than rawinsonde. That means that the TAMDAR sensor is also good at wind observation except that (observations with small speed) easily affected by heading information. So, there is some room to improve wind observation quality of TAMDAR if accurate heading information can be obtained.

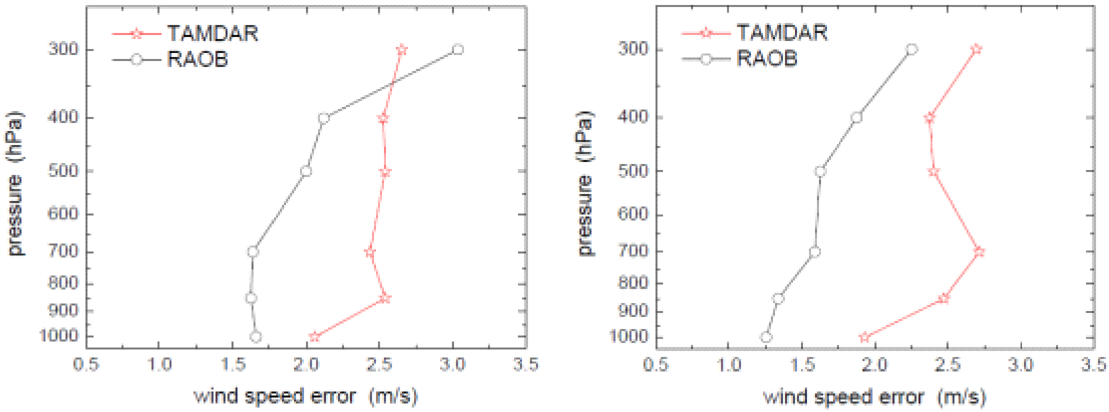

Figure 8 The same as Fig.6, but speed

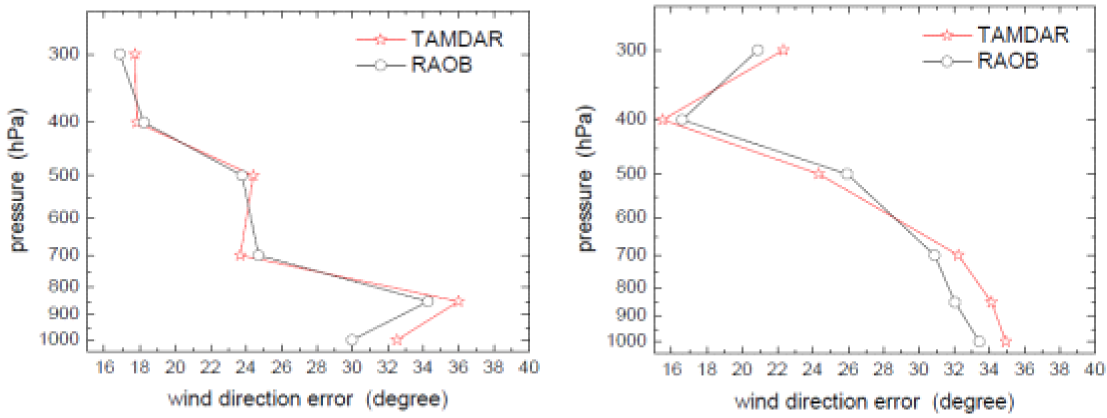

Figure 9 The same as Fig.6, but direction

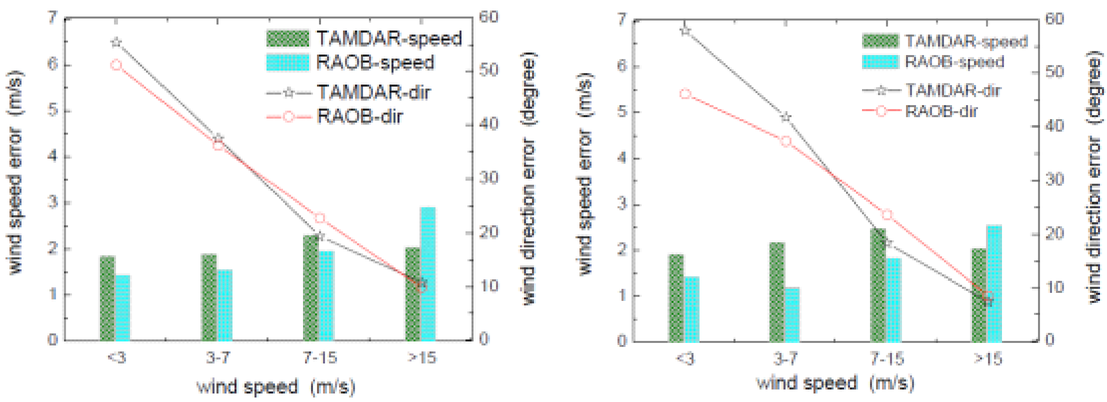

Figure 10 Speed/direction errors of TAMDAR and rawinsonde by wind speed

4. Summary and plan work

TAMDAR, Tropospheric Airborne Meteorological Data Reporting, provides thousands observations of temperature, wind, and relative humidity per day in continental United States, which will contribute to a good initial condition for numerical weather prediction. In this study, the standard deviation of TAMDAR observational error is estimated by using collocations of meteorological reports from three different data sources-rawinsonde, TAMDAR, and WRF 6-h forecast in January and June 2010.

The error estimation results reveal that the relative humidity (RH) observations error of TAMDAR is as good quality as rawinsonde in winter month and smaller than rawinsonde in summer month. Temperature observation error of 0.6-1.0°C is agreeable with a reporting error of about 1°C, and the largest difference of only 0.15 °C between rawindsonde and TAMDAR shows the good quality of TAMDAR temperature. The speed and direction error of wind observations significantly depend on wind speed. Generally, the wind observations of TAMDAR is inferior to rawinsonde. However, to be encouraging, the error of TAMDAR wind observations with speed more than 15m/s is smaller than rawinsonde.

The abundant of TAMDAR measurements with good quality will greatly complement sparse RAOB, especially RH measurements. To verify the positive impact of TAMDAR on mesoscale/convective forecast will be next work.

5. Acknowledgements

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