Cloud-scale ice supersaturated regions spatially correlate with high water vapor heterogeneities

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Abstract

Cirrus clouds have large yet uncertain impacts on Earth’s climate. Ice supersaturation (ISS) – where the relative humidity with respect to ice (RHi) is greater than 100% – is the prerequisite condition of ice nucleation. Here we use 1 Hz (~230 m) in situ aircraft-based observations from 87°N–67°S to analyze the spatial characteristics of ice supersaturated regions (ISSRs). The median length of 1-D horizontal ISSR segments is found to be very small (~1 km), which is two orders of magnitude smaller than previously reported. To understand the conditions of these small scale ISSRs, we compare individual ISSRs with their horizontally adjacent subsaturated surroundings and show that 99% and 73% of the ISSRs are moister and colder, respectively. When quantifying the contributions of water vapor (H2O) and temperature (T) individually, the magnitudes of the differences between the maximum RHi values inside ISSRs (RHi_max) and the RHi in subsaturated surroundings are largely derived from the H2O spatial variabilities (by 88%) than from those of T (by 9%). These features hold for both ISSRs with and without ice crystals present. Similar analyses for all RHi horizontal variabilities (including ISS and non-ISS) show strong contributions from H2O variabilities at various T, H2O, pressure (P) and various horizontal scales (~1–100 km). Our results provide a new observational constraint on ISSRs on the microscale (~100 m) and point to the importance of understanding how these fine scale features originate and impact cirrus cloud formation and the RHi field in the upper troposphere (UT).

1. Introduction

Cirrus clouds, located in the UT and composed of ice crystals, cover ~30% of the Earth’s surface (Wylie and Menzel, 1999). As a major uncertainty in climate modeling (Solomon et al., 2007), the magnitude and sign (cooling or warming) of cirrus clouds’ radiative forcing are not only influenced by macroscopic properties, such as coverage, thickness and height, but also by microphysical properties, such as ice crystal number density and size distribution (Liou, 1992). In order to understand the microphysical properties of cirrus clouds, it is crucial to analyze the initial conditions of cirrus cloud formation, i.e., the conditions of ISS. For example, the frequency distribution of ISS can help us to estimate the influences of different freezing mechanisms for cirrus cloud formation (Cziczo et al., 2013), while the transition from clear-sky ISS to the ISS with ice crystals can help us to understand the formation and evolution of ice crystal regions (Diao et al., 2013).

Ice nucleation happens once RHi reaches the nucleation threshold (RHi_nuc) (Koop et al., 2000; Murphy and Koop, 2005; Peter et al., 2006). By definition, RHi = e/e_s×100%, where e is the H2O partial pressure and e_s is the saturation vapor pressure. It is crucial to understand the temporal and spatial variabilities of RHi, since they determine the time and the location of ice crystal formation, respectively. However, one of the major difficulties in understanding RHi variability is that the processes influencing it range over numerous orders of magnitude in scale, from the synoptic scale (~1000 km) (e.g., Rossby waves), mesoscale (~100 km) (deep convection), microscale (~100 m, small gravity waves and turbulence) to the micrometer scale (the activation of aerosols) (Heintzenberg and Charlson, 2009; Lynch et al., 2002).

Recently, Wood and Field (2011) showed that the median chord length (1-D horizontal size) of cirrus clouds is ~1 km based on a combination of in situ aircraft observations, satellite
observations and numerical model simulations. However, it is unclear how this small-scale horizontal structure of cirrus clouds forms and what factors contribute to this feature. In particular, although ISS has been widely observed in the atmosphere over various geographical locations (Gettelman et al., 2006; Heymsfield et al., 1998; Kahn et al., 2009; Krämer et al., 2009; Lamquin et al., 2012; Vömel et al., 2002), it has not been analyzed whether the ice supersaturated regions (ISSRs, the regions with spatially continuous ISS) have the microscale structure similar to that of cirrus clouds, nor have the contributing factors been determined.

The spatial characteristics of ISSRs have only been analyzed on the mesoscale based on 1-min averaged (~15 km resolution) aircraft observations (Gierens and Spichtinger, 2000). That study concluded that the mean and median lengths of ISSR horizontal 1-D segments are ~150 km and ~50 km, respectively, and also predicted the existence of smaller ISSRs that were not sampled. Other in situ observations at higher resolution (1 Hz), such as Krämer et al. (2009) and Ovarlez et al. (2002), analyzed the RHi distribution for the integration of all the 1 Hz data, but did not address how individual ISSRs are distributed in the spatial view or what factors contribute to their spatial characteristics.

To help understand the spatial characteristics of ISSRs, it is important to understand the spatial variabilities of T and H2O, as they directly influence the spatial variabilities of RHi. Spichtinger et al. (2003) used Microwave Limb Sounder observations on the ~200 km scale and showed that ISSRs, on average, have colder T and higher moisture than subsaturated air. However, it has not been analyzed how the T and H2O spatial variabilities quantitatively contribute to the higher RHi values inside individual ISSRs. In addition, when deriving the general RHi spatial variability on the microscale, it is unknown whether H2O and T spatial variabilities have similar contributions or if one is more dominant than the other.

To compare the contributions of H2O and T to RHi variabilities, the changes of RHi are separated into the contributions from the changes of H2O and T. For example, Spichtinger et al. (2005a) and Spichtinger et al. (2005b) used radiosonde data on the ~100 km scale to analyze the formation of ISSRs in the Lagrangian view by large scale dynamics, such as gravity waves and warm conveyor belts. They pointed out the importance of large-scale cooling during the time evolution of ISSRs based on 100 km-scale Lagrangian model simulations. However, the conditions of ISSRs below the 100 km scale have not been analyzed, and it is unclear if T spatial variability is the dominant contribution to RHi spatial variability in the Eulerian view.

In this study, we analyze the individual conditions of ISSRs based on 1 Hz resolution aircraft observations. This study provides a large number of case studies of ISSRs on the microscale based on the Eulerian view in situ observations. Direct comparisons between ISSRs and their adjacent subsaturated surrounding environments are conducted in order to help understand the factors contributing to the spatial characteristics of ISSRs.

2. Data sets and instrumentation

In this work, the spatial variabilities of ISS and RHi are analyzed based on the 1 Hz (~230 m) in situ observations made from the National Science Foundation (NSF) Gulfstream-V research aircraft. Two flight campaigns are combined for a comprehensive dataset over various latitudes, altitudes and seasons. The NSF Stratosphere Troposphere Analyses of Regional Transport 2008 (START08) campaign (Pan et al., 2010) sampled the UT/LS over North America in April-June,
2008, providing ~90 transects across the thermal tropopause. The NSF HIAPER Pole-to-Pole Observations (HIPPO) Global field campaign (Wofsy et al., 2011) provided an extensive latitudinal coverage (87°N–67°S) over the central Pacific Ocean from 2009 to 2011, with ~600 vertical transects from the surface to the tropical UT or the extratropical UT/LS. The flight tracks of the START08 and HIPPO campaigns being analyzed in this study are shown in Fig. 1. Flights without H₂O observations are not shown here.

Water vapor was measured by the 25 Hz, open-path Vertical Cavity Surface Emitting Laser (VCSEL) hygrometer (Zondlo et al., 2010). The accuracy and precision of H₂O measurements are 6% and ≤ 1%, respectively. Noise levels (1σ) are typically 1–3% at 25 Hz for flight measurements. The H₂O measurements were averaged to 1s for consistency with the T measurements. The open-path design of the VCSEL hygrometer is critical for the fast response of H₂O measurements, as surface absorption and sampling problems may complicate the response time of closed-path systems. The fast response of H₂O measurements here provides the fundamental technical support to our analyses of the contributions of H₂O and T fluctuations to the RHi spatial variabilities.

Temperature measurements were recorded by the Rosemount temperature probe. The accuracy and precision of T measurements are 0.5 K and 0.01 K, respectively. The uncertainties in RHi were 8–14% at 233.15–196 K after combining the uncertainties from the VCSEL hygrometer (6%) and the T probe (± 0.5 K). The saturation vapor pressure is calculated based on Murphy and Koop (2005), which stated that all the commonly used expressions for the vapor pressure over ice are within 1% of each other at 170–273 K. We do not apply higher frequency observations to our analyses because no fast T measurements (< 1 Hz) were available in HIPPO, and the fast (sub-Hz) T measurements in START08 were complicated by the presence of ice crystal particles. For these reasons, we only use 1 Hz data in our analyses.

To compare the ISS variability between regions with and without ice crystals, we use ice crystal concentration measurements to separate these two types of regions. In START08, the ice crystal concentrations were measured by the HIAPER Small Ice Detector Probe (SID-2H) instrument (Cotton et al., 2010). The measurement range of SID-2H is 1–50 μm. During the HIPPO Global campaign deployments #2-5, ice crystal concentrations were measured by the 2DC ice probe (Korolev et al., 2011). The 2DC ice probe has a measurement range of 25–800 μm, which reports ice crystal number density Nc (in L⁻³). Since the ice crystal concentrations were not measured in HIPPO deployment #1, we only compare the ISSRs with and without the presence of ice crystals during START08 and HIPPO deployments #2-5. Here we use the terminology of “in-cloud” to represent the regions with the presence of ice crystals. We note that these terms of “in-cloud” and “clear-sky” only represent the conditions of 1-D flight segments at 1 Hz resolution. For SID-2H measurements, we define the “in-cloud” regions as locations where the total ice particle concentrations are greater than 0.06 cm⁻³ during the 1 Hz measurements. We used 0.06 cm⁻³ as the threshold for SID-2H instrument because it represents greater than one particle per second under the sampling rate of 16 cm⁻³ s⁻¹. This measurement range is where the SID-2H ice probe functions well for distinguishing between ice crystals and liquid aerosols. For 2DC measurements, we define the “in-cloud” regions to be where Nc is greater than zero. The remaining regions are considered to be “clear-sky” regions. We note that there might be a small amount of data that should be “in-cloud” but are categorized as “clear-sky” condition, but these data only contribute to a very small percentage of the total clear-sky data. For example, the SID-
2H measurements at \(0 < N_c < 0.06 \text{ cm}^{-3}\) could be either liquid aerosols or ice crystals, but these data only contribute to 1.9% of the total “clear-sky” data at \(T \leq 40 \, ^\circ\text{C}\). In addition, for 2DC probe, ice crystals smaller than 25 \(\mu\text{m}\) are not detected. But according to the measurements of SID-2H, the observations with ice crystal mean diameter < 25 \(\mu\text{m}\) is only 1.6% with respect to the total “clear-sky” data at \(T \leq 40 \, ^\circ\text{C}\). Therefore, even if these “clear sky” data were indeed clouds, they are not going to impact our results significantly. Other measurements that have been used to help interpret the results include ozone (\(O_3\)), carbon monoxide (\(CO\)) and ice water content. The analyses of \(O_3\), \(CO\) and ice water content are based on the measurements from the START08 campaign only. In START08, \(O_3\) was measured by the NCAR dual-beam ultraviolet absorption photometer with an accuracy of 5% and precision of 5% (Tilmes et al., 2010). \(CO\) was measured using the NCAR vacuum ultraviolet resonance fluorescence instrument with an accuracy of 9% and precision of 0.8 ppbv (Tilmes et al., 2010). Total water content was measured by the University of Colorado (CU) tunable diode laser hygrometer with an accuracy of 20–25% and precision of 5% (Davis et al., 2007). Ice water content (IWC) value is derived by deducting the water vapor measurements of VCSEL hygrometer from the total water content measurements of the CU hygrometer.

Because any synchronization delays between the \(H_2O\) and \(T\) measurements would impact our analyses of their contributions to the \(RHi\) fluctuations, we demonstrate the in-flight synchronization between the \(T\) and \(H_2O\) measurements with the special case of a gravity wave observed in START08 Research Flight (RF) 08 (Fig. 2). We note that this gravity wave has unusually high frequency and magnitude as well as a clearly observable wave structure, which were not typically seen during the START08 and HIPPO flight campaigns. In general, as the aircraft horizontally transects through a gravity wave near the tropopause, the \(H_2O\) concentration and \(T\) values are expected to anticorrelate with each other. In this case, the gravity wave has \(\sim 10\) oscillations with an average period of \(\sim 8 \text{ s} \, (~1800 \text{ m})\). The peaks of \(H_2O\) concentration match well with the troughs of \(T\) values in individual periods, which demonstrate that \(T\) and \(H_2O\) measurements have fast, synchronized response to the fluctuations of the atmospheric conditions at 1 Hz resolution.

3. Methods

3.1 Method for analyzing \(RHi\) spatial variability

Based on the Clausius-Clapeyron equation, the variability of \(RHi\) is directly contributed by the variabilities of \(H_2O\) and \(T\). Although previous studies have analyzed the spatial variabilities of \(T\) and \(H_2O\) (Cho et al., 2000) and the variance scaling of \(T\) and \(H_2O\) (Kahn and Teixeira, 2009; Kahn et al., 2011), it is still unclear for individual ISSRs how the higher \(RHi\) values inside ISSRs than their adjacent subsaturated air are derived from \(T\) and \(H_2O\) spatial variabilities. In addition, although it has been shown for the boundary layer that \(T\) contribution to \(RHi\) variability becomes more important from mesoscale to microscale (Price and Wood, 2002), it has not been analyzed for the \(RHi\) in the UT whether the \(T\) contribution follows similar trend.

To quantify the contributions from \(H_2O\) and \(T\) spatial variabilities to the \(RHi\) spatial variability, we separate the change of \(RHi\) (\(dRHi\)) into two parts: the contributions from \(H_2O\) partial pressure variability (\(dRHi_{q}\)) and those from \(T\) variability (\(dRHi_{T}\)). Applying the chain rule to \(dRHi\), we get:
\[
dRH_i = d \frac{e}{e_s} = ed \frac{1}{e_s} + \frac{1}{e_s} de = dRH_{iT} + dRH_{i_q}; \quad (1a)
\]

Here \(e\) is the H\(_2\)O partial pressure, and \(e_s\) is the saturation vapor pressure over ice calculated based on the equation from Murphy and Koop (2005). Because aircraft sampling is discretely distributed, we use the difference between two points as an approximation of the derivative. We assume that the magnitudes of \(d(1/e_s)\) and \(de\) terms are relatively small, so that only the first terms of the Taylor expansion are considered in Eqs. (1b) and (1c):

\[
d \frac{1}{e_s} \approx \Delta \left( \frac{1}{e_s} \right) = \frac{1}{e_{s,1}} - \frac{1}{e_{s,2}}; \quad (1b)
\]

\[
de \approx \Delta(e) = e_1 - e_2; \quad (1c)
\]

We also separate the changes in \(e\) term \((de)\) into the contributions from the variability of H\(_2\)O volume mixing ratio (H\(_2\)OMR, ppmv) and the variability of total pressure (P, Pa). Similarly, only the first terms of the Taylor expansion are considered for \(dH_2OMR\) and \(dP\), assuming that changes are relatively small. The contributions of the H\(_2\)OMR and P variabilities to \(de\) are defined as \(de_{H2OMR}\) and \(de_P\), respectively:

\[
de = d(H_2OMR*P) = P*dH_2OMR + H_2OMR*dP = de_{H2OMR} + de_P; \quad (2a)
\]

\[
dH_2OMR \approx \Delta(H_2OMR) = H_2OMR_1 - H_2OMR_2; \quad (2b)
\]

\[
dP \approx \Delta(P) = P_1 - P_2; \quad (2c)
\]

To directly compare how H\(_2\)O and T variabilities contribute to individual ISSR conditions, we compare the RH\(_i\) values inside and outside of each ISSR. We calculated the difference between the RH\(_{i_{\text{max}}}\) inside an ISSR (RH\(_{i_{\text{max_{inside}}}}\)) and the RH\(_i\) of the horizontal adjacent subsaturated regions (RH\(_{i_{\text{outside}}})\). This difference is defined as \(dRH_{i_{\text{max}}}\). Here we use the mean RH\(_i\) of the horizontally adjacent (± 1 s) subsaturated air as representative of RH\(_{i_{\text{outside}}},\) although other larger scales (e.g., ± 2 s, ± 3 s, up to ± 30 s) of subsaturated conditions have also been tested to verify our results. We apply Eqs. (1) and (2) to \(dRH_{i_{\text{max}}}\) to quantify how \(dRH_{i_{\text{max}}}\) in each ISSR segment is composed of a pair of \(dRH_{i_q}\) and \(dRH_{iT}\).

Similarly, we analyze the horizontal spatial variabilities of all RH\(_i\) (including both ISS and non-ISS) using Eqsns (1) and (2). Here the RH\(_i\) difference between the mean RH\(_i\) values of two horizontally \((dP < 1 \text{ hPa})\) adjacent segments is defined as \(dRHi\). The RH\(_i\) variability with \(dP < 10\) hPa as well as with no pressure restriction are also analyzed. Different scales of horizontal segments are analyzed from ~230 m up to ~115 km. The maximum scale of the horizontal segment is limited to 115 km (~500 s) because of the strict horizontal restriction \((dP < 1 \text{ hPa})\) and the decreasing number of consecutive flight samples with the increasing scale. We apply Equations (1) and (2) to the \(dRH_i\) of each pair of horizontal adjacent segments and quantify how the fluctuations of H\(_2\)O and T contribute to each \(dRH_i\).
3.2 Method for analyzing the mean absolute deviation of RH\textsubscript{i}

Another similar method to analyze contributions to the RH\textsubscript{i} field is to examine the variabilities around the mean value for a certain length scale. In this regard, we also analyze the RH\textsubscript{i} horizontal spatial variability in terms of the mean absolute deviation of RH\textsubscript{i} (\(\sigma_{RH\textsubscript{i}}\)). \(\sigma_{RH\textsubscript{i}}\) is calculated for individual horizontal (\(dP < 1\) hPa) segments during the aircraft sampling by comparing each 1 Hz RH\textsubscript{i} value within that segment with the mean RH\textsubscript{i} value (Eq. (3a)). The average contributions from the variabilities of H\textsubscript{2}O and T to the magnitude of \(\sigma_{RH\textsubscript{i}}\) inside this segment are defined as \(\sigma_{RH\textsubscript{i}q}\) and \(\sigma_{RH\textsubscript{i}T}\) in Eqs. (3b) and (3c), respectively. The calculations of \(\sigma_{RH\textsubscript{i}q}\) and \(\sigma_{RH\textsubscript{i}T}\) consider the signs (positive or negative) of the H\textsubscript{2}O and T contributions to \(\sigma_{RH\textsubscript{i}}\) by using the \(\text{sgn}(x)\) terms, respectively.

\[
\sigma_{RH\textsubscript{i}} = \frac{\sum_{k=1}^{N} (|RH\textsubscript{i,k} - \overline{RH\textsubscript{i}}|)}{N - 1}, \quad (3a)
\]

\[
\sigma_{RH\textsubscript{i}q} = \frac{\sum_{k=1}^{N} (\text{sgn}(x_q) |e_s - \overline{e}|)}{N - 1}, \quad (3b)
\]

\[
\sigma_{RH\textsubscript{i}T} = \frac{\sum_{k=1}^{N} (\text{sgn}(x_T) |e_{sk} - \overline{e}|)}{N - 1}, \quad (3c)
\]

\[
\text{sgn} (x_q) = 1, \text{ if } (RH\textsubscript{i,k} - \overline{RH\textsubscript{i}})(\frac{1}{e_s} (e_{sk} - \overline{e})) \geq 0,
\]

\[
\text{sgn} (x_q) = -1, \text{ if } (RH\textsubscript{i,k} - \overline{RH\textsubscript{i}})(\frac{1}{e_s} (e_{sk} - \overline{e})) \leq 0,
\]

\[
\text{sgn} (x_T) = 1, \text{ if } (RH\textsubscript{i,k} - \overline{RH\textsubscript{i}})(\frac{1}{e_{sk}} (e_s - \overline{e})) \geq 0,
\]

\[
\text{sgn} (x_T) = -1, \text{ if } (RH\textsubscript{i,k} - \overline{RH\textsubscript{i}})(\frac{1}{e_{sk}} (e_s - \overline{e})) \leq 0,
\]

where N is the sample size; \(\overline{RH\textsubscript{i}}\), \(\frac{1}{e_s}\) and \(\overline{e}\) are the mean values of RH\textsubscript{i}, \(\frac{1}{e_s}\) and e in the sampling range, respectively. Similar to the \(dRH\textsubscript{i}\) analyses of the horizontal RH\textsubscript{i} variability, the maximum scale of \(\sigma_{RH\textsubscript{i}}\) is also limited to 115 km (\(N = 500\)) because of the strict horizontal restriction (\(dP < 1\) hPa) and the decreasing number of consecutive flight samples with increasing scale. According to these definitions, when the changes in H\textsubscript{2}O concentration have the same sign as the changes in RH\textsubscript{i}, the H\textsubscript{2}O contribution to RH\textsubscript{i} fluctuation is positive, and \(\sigma_{RH\textsubscript{i}q}\) term is
positive. Similarly, when the changes in $T$ have the opposite sign as the changes in $\text{RHi}$, $\sigma \text{RHi}_T$ term is positive. The $\sigma \text{RHi}_T$ term should always be greater or equal to zero, because it is the sum of absolute values. Therefore at least one of the terms of $\sigma \text{RHi}_q$ and $\sigma \text{RHi}_T$ should be non-negative, which means that at least one of the $H_2O$ or $T$ fluctuations are positively contribute to the direction of $\text{RHi}$ fluctuation. For example, for a segment of aircraft observations of fluctuating $\text{RHi}$, when the $\text{RHi}$ value of one point is smaller than the mean $\text{RHi}$ value, there should be lower $H_2O$ concentration or higher $T$, or both, at this point with respect to the mean $H_2O$ and $T$ values of the segment. Using Eq. (3) can help us separately quantify the contributions of $H_2O$ and $T$ to the fluctuation of $\text{RHi}$, no matter the $\text{RHi}$ change is positive or negative at each point.

We note that the current method differs from the previous variability analyses of Gierens et al. (2007). Although Gierens et al. (2007) first decomposed $d\text{RHi}$ into the fluctuations of $H_2O$ and $T$ (similar to Eq. (1a) in this work), they however used the standard deviations of $H_2O$ and $T$ to compare the contributions of $H_2O$ and $T$ variabilities to $\text{RHi}$ variability. The standard deviations of $H_2O$ and $T$ do not account for the direction of their changes, and therefore cannot address whether the fluctuations of $H_2O$ and $T$ are in the same (or opposite) direction with $\text{RHi}$ fluctuation. For example, for a times series of continuously increasing $\text{RHi}$ with increasing $H_2O$ and $T$, the increasing $T$ actually provides a negative contribution to the increasing $\text{RHi}$ along the time series. But this negative contribution of increasing $T$ is treated as the same as the positive contribution of increasing $H_2O$ when comparing the standard deviations of $T$ and $H_2O$. In other words, using the expression of standard deviation for this type of analyses would overestimate the contribution to $\text{RHi}$ variability when the changes of $H_2O$ ($T$) are in the opposite (same) direction of $\text{RHi}$ changes.

4. Results and discussion

4.1 Overall aircraft sampling of ISS and ISSRs

The data distribution and sampling range of this work are shown in Table 1. The observations include ~300 hr and ~100 hr in the Northern and Southern Hemispheres (NH and SH), as well as ~310 hr and ~90 hr in the extratropical ($30^\circ S$–$67^\circ S$ and $30^\circ N$–$87^\circ N$) and tropical regions ($30^\circ S$–$30^\circ N$), respectively. The overall observations of $T$, $P$ and $H_2O$ range from 196–311 K, 133–1039 mb and 1.5–39000 ppmv, respectively. The whole dataset consists of ~217 hours of 1 Hz observations at $T \leq -40^\circ C$ (~62 hr from START08, ~155 hr from HIPPO). Unless noted otherwise, we restrict our analyses to $T \leq -40^\circ C$ to ensure that no ambiguities from supercooled liquid water are involved (Murphy and Koop, 2005). The overall distribution of the observations at $T \leq -40^\circ C$ is illustrated in Fig. 3 in the latitudinal and vertical view. Here the number of observations is binned by $10^\circ$ in latitude and 25 mb in pressure. Fig. 3 shows that our observations from the HIPPO and START08 campaigns cover a wide latitudinal range ($87^\circ N$–$67^\circ S$) and vertical range (~130–550 mb). Note that the NSF GV aircraft ceiling ($< ~15$ km) prevents us from sampling the majority of the Tropical Tropopause Layer.

Of the 217 hours at $T \leq -40^\circ C$, there are ~11 hours of ISS observations (5%). For these ISS observations, 87% and 13% of them were in the NH and SH, respectively. In addition, 90% and 10% of these ISS were observed in the extratropical and tropical regions, respectively. We note although there are fewer ISS observations in the SH and tropical regions at $T \leq -40 ^\circ C$, there are still sufficient amount of flight hours in the SH (~105 hr) and in the tropical regions (~93 hr) for
our analyses of RH variability at all T condition. The total ISS observations are composed of 1542 individual ISSR segments. Here an ISSR is defined as the 1-D segment where ISS is observed to be spatially continuous. Similar to previous analyses, ISSRs include both clear-sky and in-cloud conditions (Spichtinger et al., 2005b). For the dataset with ice particle measurements (i.e., START08 campaign and HIPPO deployments #2-5), 97% of total observations at T ≤ -40°C were in clear sky and 3% were in cloud. For the clear-sky conditions, 5% were ice-supersaturated. For the in-cloud conditions, 54% were ice-supersaturated.

To demonstrate the general consistency with past work for in-cloud measurements, we examine the probability density function (PDF) of the RHi for in-cloud conditions. The PDF of 1 Hz in-cloud RHi in START08 and HIPPO#2-5 campaigns peaks around 95.5–98.5% (Fig. 4). Ovarlez et al. (2002) analyzed 1 Hz aircraft observations at Prestwick, Scotland (55°N) and showed that the PDF of in-cloud RHi peaks at 97.5% at T ≤ -40°C, which is very consistent with our observations. Another previous study of Krämer et al. (2009) used 10% as RHi bin size for 1 Hz observation and showed that the in-cloud data peak at 100%. For the larger scale (~45 km) RHi distribution, Kahn et al. (2009) used satellite observations to show that the in-cloud RHi peaks around 80–90% in the UT. The lower value of the in-cloud RHi peak for the larger scale observations compared with the smaller scale observations is a common feature as discussed by Dickson et al. (2010), since a shallow layer of ice saturation or ISS embedded within a subsaturated layer may be averaged out by satellite retrievals due to their coarse vertical resolutions. We note that these past studies were conducted at different temperature and altitude ranges. For example, the current analyses on ISS are at 196–233.15 K; the analyses of Krämer et al. (2009) were at 183–240 K; the analyses of Ovarlez et al. (2002) were at ~210–250 K; the analyses of Kahn et al. (2009) were at T < 243 K and H2O mixing ratio < 15 ppmv, which is below ~15 km. In addition, the uncertainties from different measurements may also contribute to the differences in RHi peak, for example, the uncertainty of RHi is 8–14% in this study.

To further compare with the previous 1 Hz observations of ISS by Krämer et al. (2009), we analyze the distribution of 1 Hz RHi data at various T for both clear-sky and in-cloud conditions. We note that the observations in Krämer et al. (2009) contain much colder conditions that haven’t been sampled in the START08 and HIPPO campaigns due to the flight ceiling restriction of the GV research aircraft. Fig. 5 shows that for both conditions, the RHi observations are almost always at or below the liquid water saturation line calculated based on Murphy and Koop (2005). We note that there are a few points in Fig. 5 that have higher RHi than the liquid water saturation line, but the differences between these points and the liquid water saturation line are still within the combined uncertainties of 8–14% in RHi. In addition, the observed ISS is mostly at or below the homogeneous freezing threshold of a liquid droplet with 0.5 μm radius (Koop et al., 2000). These findings are consistent with the RHi distribution with respect to T shown in Krämer et al. (2009) at the same temperature range. We note that the low RHi values around < 20% for in-cloud data may represent ice crystals that fall into much drier conditions than their initial formation conditions. We also color coded the RHi data by H2O mixing ratio and showed that the H2O mixing ratios of most ISS observations (99%) are above 20 ppmv (orange to purple color), where complications from calibration artifacts are less problematic.

### 4.2 Spatial characteristics of ISSRs
A typical time series of the aircraft observations of RHi (black line), T (red dotted line), H₂O (blue) and altitude (green) are shown in Fig. 6A. The ISSR is defined as the region where RHi is consecutively above 100% (thick red line). For each segment of ISSR, we analyze its spatial characteristics in terms of its length and RHi\textsubscript{max}. In addition, we calculate the spacing between the ISSRs. Here these spatial characteristics are analyzed in a horizontal Eulerian view, since the aircraft’s horizontal true air speed is always at least ~25 times greater than its vertical velocity. The distributions of these characteristics of all 1542 ISSRs are shown in Fig. 6B. The number of events of ISSR length and spacing are shown as red solid dots and green upside down triangles in Fig. 6B, respectively. And the relationship between ISSR length and RHi\textsubscript{max} value is shown as the blue void triangles. Based on the number of events of ISSR length, the mean and median of ISSR length are 3.5 km and 0.7 km, respectively. These values are two orders of magnitudes smaller than the previously reported mean (150 km) and median (50 km) ISSR lengths at ~15 km resolution (Gierens and Spichtinger, 2000). Because the previous work of Wood and Field (2011) used a power law distribution to fit the distribution of 1-D cirrus cloud chord length, here we also apply a power law fit to the distribution of ISSR lengths (red dotted line in Fig. 6B), that is, \(\log_{10}(\text{Number of events of ISSR}) = a + b \times \log_{10}(\text{ISSR length})\). The intercept and slope of the fit are 4.7 ± 0.4 and -0.77 ± 0.11, respectively. The ± one sigma represents one standard deviation for all linear fit in this work. The slope -0.77 ± 0.11 of ISSR length distribution observed in this study is comparable with the slope -1.66 ± 0.06 fitted for cirrus cloud length distribution in Wood and Field (2011).

Besides the analyses on ISSR length scale, we also analyze the spacings between the ISSR segments and find them to be very small. The mean and median scales of the spacings are ~47 km and ~1 km, respectively. Similar to the fit of ISSR length, we apply a power law fit to the distribution of ISSR spacings (green dashed line in Fig. 6B), that is, \(\log_{10}(\text{Number of events of spacing}) = a + b \times \log_{10}(\text{Length of spacing})\). The intercept and slope of the fit are 3.5 ± 0.1 and -0.40 ± 0.03, respectively. The small median value of the spacings suggests that the ISSR segments are closely distributed next to each other, which indicates a very patchy, heterogeneous structure of ISSRs on the microscale that has not been reported before. The 1-D chord lengths of ISSRs cannot be directly treated as the scales of ISSRs in the higher dimensional view, because it is more likely that a larger ISSR will be transected than a smaller one (Gierens and Spichtinger, 2000). Overall, the observed 1-D segment scale of ISSRs (~1 km) is comparable to the recently observed 1-D median segment scale of cirrus clouds (~1 km) (Wood and Field, 2011), which may indicate a link between the ISS spatial variability and cirrus spatial heterogeneities.

To examine whether the larger sized ISSRs correlate with larger or smaller RHi values, we calculated the mean RHi\textsubscript{max} value of all ISSRs within each size bin, as shown by the blue void triangles in Fig. 6B. The result shows that RHi\textsubscript{max} value increases with increasing ISSR length scale. We apply a linear fit (shown as blue dotted line in Fig. 6B) to the RHi\textsubscript{max} value versus the log scale ISSR length, that is, \(\text{RHi}_{\text{max}} = a + b \times \log_{10}(\text{ISSR length})\). The intercept and slope of the fit are 64 ± 5 and 14 ± 1, respectively. Although not shown here, the mean RHi values inside ISSRs also increase as the scales of ISSR segment lengths increase. These findings indicate that large scale observations may have biases in estimating RHi\textsubscript{max} if the small scale ISSR segments have been averaged out due to coarse sampling resolution. The correlation between RHi\textsubscript{max} and the ISSR scale shows the importance of understanding the scales of the processes that contribute to the formation of ISSRs, since the scales of the processes might not only influence the size of ISSRs but also their RHi\textsubscript{max} value.
4.3 Contributions of H$_2$O and T spatial heterogeneities to microscale ISSRs

To help quantify the observed horizontal patchiness of ISSRs, we analyze how the higher RHi inside each ISSR segment occurs comparing to the horizontally adjacent subsaturated regions (non-ISSRs). The RHi differences between ISSRs and non-ISSRs fundamentally result from the differences in T and H$_2$O in these regions. There are three ways that a region becomes an ISSR: 1) colder and moister (in terms of absolute H$_2$O concentration), 2) colder and drier, or 3) warmer and moister than adjacent non-ISSRs. We note although theoretically case 2 and case 3 include the situation of H$_2$O$_{in}$ = H$_2$O$_{out}$ and T$_{in}$ = T$_{out}$, respectively, this situation almost never happens given the high precision of H$_2$O and T measurements. We categorize the horizontal ISSRs into these three types, which include 1094 ISSRs on quasi-isobaric levels (dP < 1 hPa). In total, 99% of 1094 horizontal ISSRs have higher H$_2$O inside than outside (cases 1+3), and 73% have lower T inside than outside (cases 1+2) (Fig. 7A). Thus, the ISSRs with higher H$_2$O concentrations are more frequent than those with lower T.

The frequency analyses above of being colder or moister do not yet address the contributions of H$_2$O and T in determining the magnitude of the higher RHi inside each ISSR. Therefore, these contributions need to be placed in comparable terms from Equation (1). The $d$RHi$_{max}$ in each ISSR segment is contributed by a pair of $d$RHi$_q$ (Fig. 7B, blue dot) and $d$RHi$_T$ (red dot). The slopes of the linear fits represent the ratio of the total contributions, which are 0.88 ± 0.006 and 0.09 ± 0.005 for H$_2$O and T, respectively. Thus the higher RHi$_{max}$ magnitude inside ISSRs compared to outside is mainly (88%) contributed by H$_2$O variability. The sum of slopes does not exactly equal one since we only consider the first terms of the Taylor expansion of the derivatives of e and 1/e (see Section 3.1). We note that for the linear fit of $d$RHi$_q$ or $d$RHi$_T$, the (%) sign in the intercept is omitted in order to be consistent with the RHi value on the ordinate. For example, the intercept for the fit of $d$RHi$_q$ in Fig. 7B stands for 0.19 ( %) ± 0.07 (%), which is very close to zero. This is because that when $d$RHi$_{max}$ approaches zero, the $d$RHi$_q$ and $d$RHi$_T$ term should also approach zero. The $d$RHi$_q$ term is further analyzed by quantifying the contributions from total pressure and H$_2$O volume mixing ratio using Equation (2) (Fig. 7C). The changes in H$_2$O partial pressure (de) are almost exclusively (100% ± 0.01%) the result of the changes of H$_2$O mixing ratio and not due to total pressure changes.

The above analyses compared ISSRs with their horizontally adjacent (dP < 1 hPa) subsaturated air (non-ISSRs) within ±230 m from the ISSR boundary. In order to demonstrate that the strong contribution of H$_2$O heterogeneities to $d$RHi$_{max}$ does not vary with the lengths of the non-ISSRs being chosen for the comparisons, we tested our result with various lengths of horizontal adjacent non-ISSRs, ranging from ~230 m to 6.7 km. Beyond ~6.7 km length, the intersection with adjacent ISSR segments limits the data availability. The contribution of H$_2$O heterogeneities does not vary significantly with the scales of non-ISSRs being chosen for the comparison (Fig. 8).

Considering that the formation of ice crystals inside air parcels can change the distribution of H$_2$O by depleting the vapor phase, we also analyze how the presence of ice crystals would change the correlations between high H$_2$O heterogeneities and ISS in the Eulerian view. Using data from the START08 and HIPPO#2-5 campaigns when ice crystals were measured, the ISSRs are separated into regions with and without the presence of ice crystals. The contributions of H$_2$O and T variabilities to $d$RHi$_{max}$ in these two types of ISSRs are analyzed. For these analyses,
\(dRHi_{\text{max}}\) represents the difference between the \(RHi_{\text{max}}\) value of ISSRs and the mean \(RHi\) of the horizontally adjacent (± 230 m) subsaturated air. For both the ISSRs with and without the presence of ice crystals, \(H_2O\) variability is the dominant contributor to \(dRHi_{\text{max}}\) (Fig. 9). These results demonstrate that the strong contributions of \(H_2O\) heterogeneities to the spatial characteristics of ISSRs exist before, during and after ice nucleation.

### 4.4 Horizontal spatial variability of all \(RHi\) and the contributions from \(H_2O\) and \(T\) spatial variability

Because ISS ultimately derives from non-ISS (subsaturated and saturated) conditions, we further compare the \(RHi\) horizontal variabilities between ISS (Fig. 10A) and non-ISS (Fig. 10B) conditions. Based on Equation (1), we analyze the contribution from \(H_2O\) and \(T\) to the horizontal \(RHi\) variabilities in terms of \(dRHi\). Here \(dRHi\) represents the difference of the mean \(RHi\) values between one segment and its adjacent segment in the horizontal \((dP < 1 \text{ hPa})\). The analyses of 1 Hz \(dRHi\) show large contributions from \(H_2O\) horizontal variabilities for both ISS \((0.93 \pm 0.005)\) and non-ISS \((0.94 \pm 0.002)\) conditions. In addition, if we combine the ISS and non-ISS conditions and analyze the spatial variabilities of all \(RHi\) at 1 Hz scale (Fig. 11A), \(H_2O\) spatial variabilities contribute \(0.93 \pm 0.004\) to the \(RHi\) variations. We also analyzed the contribution of \(H_2O\) variability to the variability of all \(RHi\) with two less tight pressure restrictions: 1) \(dP < 10\) hPa and 2) no pressure restriction. The results show that the \(H_2O\) contribution to \(dRHi\) for these two scenarios are \(0.93 \pm 0.0004\), \(0.93 \pm 0.0004\) at 1 Hz scale, and \(0.84 \pm 0.01\), \(0.89 \pm 0.03\) at 23 km scale, respectively. These results suggest that the pressure restriction does not influence our conclusion of the strong contribution of \(H_2O\) variability to the \(RHi\) variability.

To demonstrate that the contribution of \(H_2O\) spatial variability to \(dRHi\) is not an artifact of instrumental noise, we filtered the 1 Hz data with \(|\Delta H_2O_{\text{ppmv}}|/H_2O_{\text{ppmv}} \leq 3\%\). After removing these data, the contribution of \(H_2O\) horizontal variability to 1 Hz horizontal \(dRHi\) does not vary significantly, which is \(0.96 \pm 0.001\). We note that the precision of the \(H_2O\) measurement is often < 1\%, which is much smaller than the criteria used here, so that we are likely removing real atmospheric fluctuations with this procedure. Similarly, when putting a very tight quality control on the precision of \(T\) measurement by filtering out the 1 Hz data with \(|\Delta T| \leq 0.1\ K\), the contribution of \(H_2O\) horizontal variability to 1 Hz horizontal \(dRHi\) does not vary significantly either, which is \(0.82 \pm 0.003\). Thus, even if the variabilities of \(H_2O\) and \(T\) well above the instrumental precision are filtered out, the \(H_2O\) horizontal variabilities always have large contributions to the \(RHi\) horizontal variabilities.

Another method of examining the \(RHi\) variabilities is to quantify the absolute deviation from a mean for both ISS and non-ISS conditions (see Equations (3)). Here \(\sigma RHi\) represents the mean of the absolute differences between each 1 Hz \(RHi\) and the average \(RHi\) value within a certain horizontal segment. For example, at ~2.3 km scale, the \(\sigma RHi\) analyses show that a ratio of \(0.92 \pm 0.001\) of the 1 Hz \(RHi\) horizontal variabilities is contributed by the \(H_2O\) horizontal variabilities (Fig. 11B). To test whether our results hold for all cloud scales, various scales of \(dRHi\) and \(\sigma RHi\) are chosen. From ~230 m up to ~115 km, the results all show much larger contributions from the \(H_2O\) horizontal variabilities (~0.9–0.8) to the \(RHi\) horizontal variabilities than from the \(T\) horizontal variabilities (~0.1–0.2) (Fig. 11C).
The above analyses of RHi spatial variability are restricted to T ≤ -40°C. To expand our analyses of RH spatial variability to various vertical levels, we binned the data by ranges of T (193–273.15 and >273.15 K binned by 20 K), H2O (<10, 10–30, 30–100, 100–1000, >1000 ppmv) and P (133–200 and 200–1000 hPa binned by 200 hPa). We apply the dRHi analyses at 1 Hz scale to all the relative humidity (RH) observations from the surface to the UT/LS. The results in Table 2 show that the H2O horizontal variabilities always have dominant contributions to RH horizontal variabilities, and these H2O contributions decrease slightly from the surface to the UT/LS, e.g., from 0.94 ± 0.001 at > 800 hPa to 0.90 ± 0.001 at 0–200 hPa. Although not shown in Table 2, the standard deviations of all the dRHi_T and dRHi_q values are smaller than the last digit of these fits. This finding is consistent with the previous findings about the decreasing variances of H2O concentrations from the surface to the UT region (Cho et al., 2000; Kahn and Teixeira, 2009; Kahn et al., 2011). In order to examine whether the dominant contribution of H2O variability varies with latitudes, seasons and between over land and ocean, we analyzed the contribution of H2O and T variabilities to the 1 Hz dRHi at different P bins. Table 3 shows that the H2O variability contribution at each pressure bin does not vary significantly when binned by latitude (0–30°N, 30°N–60°N, 60°N–87°N, 0–30°S, 30°S–60°S, 60°S–67°S), nor does it vary between observations over land and ocean, or at different times of a year.

4.5 Dynamical conditions of ISS with tracer-tracer correlation analyses

To understand the scales of the dynamics that influence the formation of ISSRs, we examine two independent pairs of conservative tracers in extratropical regions, that is, the O3-CO correlation (Pan et al., 2004) and the total water content (H2Otot)-wet equivalent potential temperature (θ_e) correlation (Paluch, 1979). The θ_e values are calculated based on the equations given in Appendix Section 1. For both tracer-tracer correlations in Fig. 12, the grey background points represent the observations including both ISS and non-ISS, while the colored markers represent ISS observations with each type of marker representing one flight. In general, the values of tracer correlations should remain constant (i.e., a single point in the correlation plot) if air parcels are sampled from the same origin (i.e., same chemical tracer values). Otherwise, if mixing between air parcels from different origins has occurred, the correlation between the tracers follows a line or curve.

The O3-CO correlation can be used to highlight stratospheric-tropospheric mixing. According to Pan et al. (2004), we define the chemical tropospheric and stratospheric regions based on the O3-CO correlations in START08. The chemical troposphere is defined by the linear fit to O3 < 70 ppbv, that is, y = a + b × x, where y is O3 (ppbv), and x is CO (ppbv). Here a is 47.0 ± 0.1, b is 0.063 ± 0.010, and the standard deviation of the residuals (σ_y) is 10.5. The stratospheric branch is fitted by a quadratic polynomial fit: x = a_0 + a_1y + a_2y^2, where y is O3 (ppbv), and x is CO (ppbv). σ_x is the standard deviation of the residuals. Here a_0 = 15.0 ± 0.2, a_1 = 0.0299 ± 0.0005, a_2 = -2.37E-05 ± 3E-7, and σ_x = 0.667. Above the fit of chemical troposphere and on the right hand side of the fit of chemical stratosphere is the extratropical transition layer (Pan et al., 2004). In Fig. 12A, the linear fit of the chemical troposphere and ± 3 σ_y of the fit are shown as the black and red dotted lines, respectively. We note that Fig. 12A is only a part of the whole O3-CO tracer plot and therefore the fit of the chemical stratosphere is not shown in Fig. 12A. All the ISS observations in START08 happened either in the chemical troposphere or in the transition layer. The results show that most of the ISS observations (colored markers) from individual flights follow almost straight mixing lines. The extrapolations of these mixing lines can help determine
the origins of air parcels being mixed. For example, the O$_3$-CO mixing lines with positive slopes represent tropospheric-tropospheric mixing (RF09, 16, 17 in Fig. 12A), since the extrapolations of the mixing lines intercept tropospheric air at the two ends. On the other hand, the mixing lines with negative slopes represent stratospheric-tropospheric mixing (RF11, 15 in Fig. 12A), since their extrapolations intercept stratospheric air at one end and tropospheric air at the other (such as discussed in Zahn et al. (2004)).

The O$_3$-CO correlation captures the stratospheric-tropospheric mixing well, but to highlight the tropospheric-tropospheric mixing, H$_2$O$_{tot}$-$\theta_q$ correlation is also analyzed here. In general, the background of the atmosphere from the surface to the UT/LS is represented as a “C” shape in the H$_2$O$_{tot}$-$\theta_q$ correlation (i.e., the grey background in Fig. 12B). The combination of high H$_2$O$_{tot}$ and low $\theta_q$ values (upper left region) represent the tropospheric region, while the combination of low H$_2$O$_{tot}$ and high $\theta_q$ values (lower right region) represent the stratospheric region. Compared with the ISS distributions in O$_3$-CO correlation, the ISS distributions in H$_2$O$_{tot}$-$\theta_q$ correlation (colored markers in Fig. 12B) follow mixing lines that deviate slightly from the straight mixing lines, which imply that the specific entropy of the air is not fully conserved. For example, if irreversible processes happen, including external inputs of sensible and/or latent heat and phase change, the mixing lines would deviate from a straight line. Based on the extrapolations of the observed mixing lines, negative and positive slopes represent tropospheric-tropospheric (RF09, 16, 17 in Fig. 12B) and stratospheric-tropospheric (RF11, 15 in Fig. 12B) mixing, respectively.

Most ISS mixing lines are straight, and their end points are far apart from each other, which indicate that the formation of ISS involves the mixing of two distinctively different types of air parcels (see Appendix section 2). This feature could be explained by the previous findings that large scale uplift usually plays an important role in ISSR formation (Spichtinger et al., 2005a, 2005b). The evenly distributed points along the mixing lines show that the air parcels have been well mixed on the small scale, since otherwise clusters of points would be observed at the two end points. This result is consistent with the previous simulation which shows that small scale turbulence and eddies play important roles in triggering ISS formation and the subsequent ice freezing events (Fusina and Spichtinger, 2010). Thus, both large- and small-scale processes play important roles in setting the environment of ISSR formation. On the one hand, uplifting and cooling provide the environments for ISSR formation on the mesoscale, and contribute to the increase of RHi in the Lagrangian view (Spichtinger et al., 2005a, 2005b). On the other hand, small-scale processes contribute to the microscale structure of ISSRs. For example, one possible cause of the microscale H$_2$O spatial variability might be the widely observed turbulence in the troposphere (Gage and Nastrom, 1986; Nastrom and Gage, 1985; Nastrom et al., 1986). Yet we caution that high resolution measurements of 3-D wind fields are needed to fully understand the cause of the microscale spatial variability of H$_2$O field in the future.

**4.6 Eulerian view examples of using H$_2$O and T variabilities to derive RHi variabilities**

Here we use one example to demonstrate that the importance of H$_2$O horizontal variabilities when deriving the RHi horizontal variabilities in the Eulerian view (Fig. 13). Fig. 13A shows a typical time series of RHi (black solid line), T (purple cross) and H$_2$O (light blue dashed line) during a flight. The grey area in Fig. 13A and C represents the ISSRs. If one only uses T spatial fluctuations in the Eulerian view to derive RHi spatial variability and neglect the H$_2$O spatial fluctuations (Fig. 13B red short dashed line), the generated ISS occurrences (Fig. 13B) would be
much lower compared with those in real observations (Fig. 13A). In addition, if one uses T fluctuations to compensate for the neglected H₂O fluctuations, even though the RHi field is the same, the generated T in ISSRs would be unnecessarily much lower (by up to ~2 K in this example, Fig. 13C) than the observed T in ISSRs (Fig. 13A). We note that for this example, the uncertainty in RHi is ~13%. Yet regardless of the uncertainties in RHi, the contribution of H₂O variability to the variability of RHi would still be dominant even if all RHi values in this time series are lowered or increased by 13% altogether. The artificially lower T inside the ISSRs in this case will lead to unrealistic conditions for ice nucleation, given the sensitivities of ice crystal growth rate and small scale turbulences to the T field. Thus it is critical that the spatial variabilities of H₂O are considered instead of being neglected or compensated by T spatial variabilities. The extent of H₂O horizontal variabilities may be a useful observational constraint to compare the 4-D cloud microphysics models with 1-D aircraft observations.

5. Atmospheric implications and future work

The formation of the microscale ISSRs are likely attributed to many dynamical processes on various scales. For example, on the microscale, processes such as small scale turbulence, small gravity waves, entrainment mixing and ice crystal sedimentation could generate the microscale spatial variability of H₂O, which defines the location and magnitude of microscale ISSRs in the horizontal Eulerian view. On the other hand, mesoscale processes such as uplifting, large scale gravity waves and deep convection could contribute to the overall environment of cooling, which lower T and increase RH in the Lagrangian view. Future work is needed on both scales in order to quantify the contribution of individual processes to the formation of ISSRs. For example, back trajectory analyses are needed to assess the roles of large scale dynamics in setting the overall cooling environment, while tracer analyses are needed to assess the roles of turbulence and mixing between air masses in contributing to the heterogeneities of H₂O field. In particular, specific case studies will be helpful in order to quantify the scales of vertical displacements that can generate the observed H₂O variability based on a local H₂O profile.

Our results show that although the dynamic causes of H₂O variabilities may differ, the strong correlation between RHi and H₂O horizontal variabilities holds at each horizontal layer from the surface to the extratropical UT/LS and tropical UT, from 87°N to 67°S, and is applicable for all cloud scales (~0.23–115 km). This ubiquitously observed feature provides a unique validation method for cloud and climate models on ISS spatial variability. In particular, currently there are various small-scale dynamics considered in the cloud models (Jensen and Pfister, 2004; Spichtinger and Krämer, 2012), as well as various parameterization schemes used to generate ISS sub-grid variability in the climate models (Kärcher and Burkhardt, 2008; Wang and Penner, 2010). Recent results from some cirrus cloud models showed that including the ISS generated by small-scale dynamical processes can have large impacts on cloud microphysics and ice crystal properties (Jensen and Pfister, 2004; Spichtinger and Krämer, 2012). Climate models also showed that the inclusion of sub-grid scale ISS variability can modify the cloud radiative forcing on the atmosphere (Kärcher and Burkhardt, 2008; Wang and Penner, 2010). In fact, most cloud models (Jensen and Pfister, 2004; Jensen, 2005) and climate models (Kärcher and Burkhardt, 2008; Wang and Penner, 2010) have been using T variability as one of the main constraints for ISS variability, because not only it is commonly accepted that the decrease of T drives the increase of RHi in a mass-conservative Lagrangian view, but also it is known that the mesoscale (~100’s km) T fluctuations have been widely observed in the UT/LS (Gary, 2006). Future work is needed to compare the simulation results with the observations on the contribution of H₂O.
spatial variability to RH\textit{i} spatial variability in each horizontal layer. Understanding how the
spatial H\textsubscript{2}O variability comes about, and why it is such a dominant factor in the Eulerian view
of RH\textit{i} field, will require future modeling studies and ultimately more accurate cloud models.

\textbf{Appendix}

\textbf{1. Calculation of wet equivalent potential temperature ($\theta_{W}$)}

We here show the derivation of $\theta_{W}$ that has been used in our analyses. At $T \leq -40^{\circ}C$, air
parcels contain dry air, water vapor and ice particles with no supercooled liquid water (Murphy
and Koop, 2005). The entropy of air can be expressed as:

$$s = s_d + q_s v + r_{ice} s_{ice}, \quad (A1)$$

where $s_d$, $s_v$ and $s_{ice}$ are the specific entropy of dry air, water vapor and ice, respectively. $q$
and $r_{ice}$ are the mass mixing ratios of water vapor and ice (kg/kg), respectively.

$$s_d = C_{pd} \ln T - R_d \ln P_d, \quad (A2)$$

$$s_v = C_{pv} \ln T - R_v \ln e, \quad (A3)$$

$$s_{ice} = C_{ice} \ln T, \quad (A4)$$

where $R_d$ (287 J kg\textsuperscript{-1} K\textsuperscript{-1}) and $R_v$ (461 J kg\textsuperscript{-1} K\textsuperscript{-1}) are the gas constants for dry air and water
vapor, respectively (Emanuel, 1994). $P_d$ and $e$ are dry air and water vapor partial pressures (Pa),
respectively. $C_{pd}$ (1004 J kg\textsuperscript{-1} K\textsuperscript{-1}), $C_{pv}$ (1870 J kg\textsuperscript{-1} K\textsuperscript{-1}) and $C_{ice}$ (J kg\textsuperscript{-1} K\textsuperscript{-1}) are the specific heats
of dry air at constant pressure, water vapor at constant pressure and ice, respectively (Emanuel,
1994). $C_{ice}$ is calculated based on the value of molecular heat capacity of ice ($C_{p,ice}$). Here the
calculation of $C_{p,ice}$ at $T > 20$K is shown as below (Emanuel, 1994; Giauque and Stout, 1936):

$$C_{p,ice} = -2.0572 + 0.14644T + 0.06163T \exp\left(-\frac{T}{125.1}\right), \quad (A5)$$

where $T$ is temperature in K and $C_{p,ice}$ is in J kg\textsuperscript{-1} K\textsuperscript{-1}. We use $T = -51.8^{\circ}C$ (mean temperature
in START08) and get $C_{p,ice} = 31.0$ J mol\textsuperscript{-1} K\textsuperscript{-1}, thus $C_{ice} = 1.75 \times 10^3$ J kg\textsuperscript{-1}

Based on the definition of wet equivalent potential temperature ($\theta_{W}$) in Emanuel (1994)
equation 4.5.11 for warm clouds (mixture of liquid water droplets, water vapor and dry air), we
derive our $\theta_{W}$ for cold clouds (mixture of ice particles, water vapor and dry air at $T \leq -40^{\circ}C$). Our
calculation of $\theta_{W}$ is shown as below and it applies to the entire RH\textit{i} range from subsaturation to
supersaturation:

$$\theta_{W} = T(\frac{P_0}{P_d})^{\frac{R_d}{C_{pd}}} \left(\frac{R_Hi}{100}\right)^{\frac{qR_v}{C_{pv} + qR_v}} \exp\left(\frac{L_{ice} q}{C_{pd} + QC_{ice}} T\right), \quad (A6)$$

where $P_0$ is the reference pressure of 1000 mb; the total water content $Q$ is defined as $Q = q$
$+ r_{ice}$; $L_{ice}$ is the latent heat of sublimation. The function of $L_{ice}$ for $T > 30$K is as below (Murphy
and Koop, 2005):
\[ L_{\text{ice}} = 46782.5 + 35.8925T - 0.07414T^2 + 541.5 \exp\left(-\frac{T}{123.75}\right), \quad (A7) \]

where \( T \) is temperature in K. We use \( T = -51.8^\circ\text{C} \) (mean temperature in START08) and get \( L_{\text{ice}} = 5.11 \times 10^4 \text{ J mol}^{-1} \text{ K}^{-1} \), thus \( L_{\text{ice}} = 2.84 \times 10^6 \text{ J kg}^{-1} \text{ K}^{-1} \). Equation (A6) applies for all conditions: subsaturation, saturation and supersaturation as well as both clear-sky and in-cloud conditions.

2. Mixing line mechanism

Chemical tracers inside the parcels can be considered to be conservative tracers if they have much longer lifetimes than the mixing time scale. For example, \( \text{O}_3 \) and \( \text{CO} \) can be used as tracers of tropospheric and stratospheric air, respectively. If the research aircraft samples through a region that contains air parcels from very different origins, this mixing feature will show up in the tracer-tracer correlation plot as a curve or line, which means that the concentrations of conservative properties show variations along the sampling transect. If there is no mixing process, the correlation plot should show almost the same values throughout. Whether the mixing feature will appear as a curve or a straight line in the correlation plots is determined by the number of different levels of air that are mixed altogether. The straight line represents mixing of air parcels only from two levels, while the curve represents mixing of air from more than two levels (Paluch, 1979). In the case of mixing of two levels, we use \( X \) and \( Y \) to represent the two conservative properties, and subscripts 1 and 2 to represent two air parcels. The conserved properties after mixing (\( X' \) and \( Y' \)) can be calculated as:

\[
X' = f_1X_1 + f_2X_2, \\
Y' = f_1Y_1 + f_2Y_2,
\]

where \( f_1 \) and \( f_2 \) are the fractions of a unit mass of the final mixture constituted by fluid originally contained by parcel 1 and 2, respectively. By mass conservation, \( f_1 + f_2 = 1 \). The ratio of the two conserved properties \( X \) and \( Y \) after mixing follows a certain relationship as below:

\[
Y' = X', \frac{Y_2 - Y_1}{X_2 - X_1} + Y_1 - \frac{X_1(Y_2 - Y_1)}{X_2 - X_1}.
\]

The correlation of \( Y(X) \) has a constant slope, \( \frac{Y_2 - Y_1}{X_2 - X_1} \), which is only defined by the initial values of \( X_1, X_2, Y_1 \) and \( Y_2 \). The intercept of the correlation is \( Y_1 - \frac{X_1(Y_2 - Y_1)}{X_2 - X_1} \), which is also a constant. The values of the conservative properties along the straight mixing line are bounded by the original values at the two levels. Therefore, by extrapolating the mixing lines the origins of the mixed air can be coarsely estimated (Paluch, 1979; Pan et al., 2004).

To demonstrate that the mixing between more than two levels would not follow a straight line, we show the example of three-level mixing. Here \( X \) and \( Y \) still represent the two
conservative properties and subscripts 1, 2 and 3 represent three air parcels, then the conserved properties after mixing (X’ and Y’) can be calculated as:

\[ X' = f_1 X_1 + f_2 X_2 + f_3 X_3, \]
\[ Y' = f_1 Y_1 + f_2 Y_2 + f_3 Y_3, \]

where \( f_1, f_2 \) and \( f_3 \) are the fractions of a unit mass of the final mixture constituted by fluid originally contained by parcels 1, 2 and 3, respectively. By mass conservation, \( f_1 + f_2 + f_3 = 1 \). In this case there are five variables \( (X, Y, f_1, f_2, f_3) \) in three equations. Therefore Y is not only a function of X but also depends on the ratio of the mixing. The function of \( Y(X, f_3) \) is shown as below (similar functions can be derived for \( Y(X, f_1) \) and \( Y(X, f_2) \)):

\[ Y' = X' \left( \frac{Y_2 - Y_1}{X_2 - X_1} \right) + f_3 (Y_1 - Y_1) - \frac{(Y_2 - Y_1)(X_1 - X_1)}{(X_2 - X_1)} + Y_1 - \frac{X_1 (Y_2 - Y_1)}{X_2 - X_1} . \]

The \( Y(X, f_3) \) correlation function will not follow a straight line in the correlation plot since it is highly unlikely that \( f_3 \) (or \( f_1, f_2 \)) will be constant within the mixing region as the mixing inside the region is not strictly uniform everywhere.

Acknowledgments

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References


Fusina, F. and Spichtinger, P.: Cirrus clouds triggered by radiation, a multiscale phenomenon, Atmospheric Chemistry and Physics, 10(11), 5179–5190, doi:10.5194/acp-10-5179-2010, 2010.


Table 1. Data distribution and sampling range in this work

<table>
<thead>
<tr>
<th>Data distribution</th>
<th>NH (0°-87°N)</th>
<th>SH (0°-67°S)</th>
<th>Tropics (30°S-30°N)</th>
<th>Extratropics (30°N-87°N, 30°S-67°S)</th>
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</thead>
<tbody>
<tr>
<td>Flight hour of all T range (hr)</td>
<td>296.9</td>
<td>104.9</td>
<td>92.6</td>
<td>309.2</td>
</tr>
<tr>
<td>Flight hour of T ≤ -40°C (hr)</td>
<td>136.3</td>
<td>31</td>
<td>21.4</td>
<td>145.9</td>
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<tr>
<td>ISS observation (hr)</td>
<td>9.3</td>
<td>1.5</td>
<td>1.0</td>
<td>9.8</td>
</tr>
<tr>
<td>T (K) min; max</td>
<td>204.2; 311.0</td>
<td>195.9; 305.3</td>
<td>204.4; 311.0</td>
<td>195.9; 309.6</td>
</tr>
<tr>
<td>P (mb) min; max</td>
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<td>134; 1024</td>
<td>133; 1039</td>
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<tr>
<td>H₂O (ppmv) min; max</td>
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<td>1.45; 38900</td>
<td>2.41; 38900</td>
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<td>H₂O (ppmv)</td>
<td>dRHi₂</td>
<td>dRHi₃</td>
<td>T (°C)</td>
<td>dRHi₂</td>
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<tr>
<td>------------</td>
<td>-------</td>
<td>-------</td>
<td>--------</td>
<td>-------</td>
</tr>
<tr>
<td>0 – 10</td>
<td>0.73</td>
<td>0.27</td>
<td>-80 – 60</td>
<td>0.88</td>
</tr>
<tr>
<td>10 – 30</td>
<td>0.89</td>
<td>0.11</td>
<td>-60 – 40</td>
<td>0.94</td>
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<tr>
<td>30 – 100</td>
<td>0.90</td>
<td>0.10</td>
<td>-40 – 20</td>
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<tr>
<td>100 – 1000</td>
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<td>0.046</td>
<td>-20 – 0</td>
<td>0.97</td>
</tr>
<tr>
<td>&gt; 1000</td>
<td>0.96</td>
<td>0.038</td>
<td>&gt; 0</td>
<td>0.94</td>
</tr>
</tbody>
</table>

**Table 2.** Contributions of H₂O and T horizontal variabilities to RH horizontal variabilities at various T, H₂O and P ranges

<table>
<thead>
<tr>
<th>P (hPa)</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 200</td>
<td>0.92</td>
<td>0.08</td>
<td>0.83</td>
<td>0.17</td>
<td>0.85</td>
<td>0.16</td>
<td>0.96</td>
<td>0.039</td>
</tr>
<tr>
<td>200 – 400</td>
<td>0.98</td>
<td>0.015</td>
<td>0.94</td>
<td>0.056</td>
<td>0.95</td>
<td>0.051</td>
<td>0.98</td>
<td>0.019</td>
</tr>
<tr>
<td>400 – 600</td>
<td>0.98</td>
<td>0.023</td>
<td>0.97</td>
<td>0.033</td>
<td>0.97</td>
<td>0.026</td>
<td>0.98</td>
<td>0.026</td>
</tr>
<tr>
<td>600 – 800</td>
<td>0.96</td>
<td>0.045</td>
<td>0.95</td>
<td>0.048</td>
<td>0.96</td>
<td>0.039</td>
<td>0.97</td>
<td>0.029</td>
</tr>
<tr>
<td>&gt; 800</td>
<td>0.93</td>
<td>0.075</td>
<td>0.94</td>
<td>0.059</td>
<td>0.94</td>
<td>0.063</td>
<td>0.94</td>
<td>0.066</td>
</tr>
</tbody>
</table>

**Table 3.** Contributions of H₂O and T horizontal variabilities to RH horizontal variabilities at various P ranges at different latitudes, over land and ocean and at different times of a year

<p>| | | | | | | |
| | | | | | | |
| Land | Ocean | | | | | |</p>
<table>
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<tr>
<th>P (hPa)</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
<th>dRHi₂</th>
<th>dRHi₃</th>
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<th>dRHi₃</th>
</tr>
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<tr>
<td>0 – 200</td>
<td>0.83</td>
<td>0.17</td>
<td>0.94</td>
<td>0.066</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>200 – 400</td>
<td>0.94</td>
<td>0.059</td>
<td>0.98</td>
<td>0.023</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>400 – 600</td>
<td>0.96</td>
<td>0.045</td>
<td>0.98</td>
<td>0.017</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>600 – 800</td>
<td>0.94</td>
<td>0.057</td>
<td>0.97</td>
<td>0.033</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt; 800</td>
<td>0.94</td>
<td>0.063</td>
<td>0.94</td>
<td>0.059</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

**Table 4.** Contributions of H₂O and T horizontal variabilities to RH horizontal variabilities at various P ranges at different latitudes, over land and ocean and at different times of a year

| P (hPa) | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ | dRHi₂ | dRHi₃ |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 0 – 200 | 0.94  | 0.061 | 0.87  | 0.13  | 0.97  | 0.031 | 0.93  | 0.074 | 0.93  | 0.064 | 0.79  | 0.21  |
| 200 – 400 | 0.93 | 0.069 | 0.94  | 0.062 | 0.98  | 0.025 | 0.97  | 0.026 | 0.96  | 0.036 | 0.94  | 0.06 |
| 400 – 600 | 0.99 | 0.012 | 0.97  | 0.026 | 0.98  | 0.021 | 0.98  | 0.019 | 0.97  | 0.026 | 0.95  | 0.053 |
| 600 – 800 | 0.98 | 0.025 | 0.96  | 0.041 | 0.97  | 0.029 | 0.96  | 0.037 | 0.96  | 0.044 | 0.92  | 0.081 |
| > 800     | 0.94  | 0.064 | 0.94  | 0.061 | 0.93  | 0.066 | 0.94  | 0.059 | 0.94  | 0.06  | 0.94  | 0.061 |

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Figure 1. Google map of START08 and HIPPO flights analyzed in this study. Yellow lines represent flight tracks of HIPPO#1-5 campaign and green lines represent the flight tracks of Research Flights 4-18 (RF04-RF18) in START08.

Figure 2. In-flight synchronization between temperature (T) and water vapor (H$_2$O) measurements. Fluctuations in T (red) and H$_2$O (purple) due to a gravity wave were observed during RF08 of START08. These fast fluctuations demonstrate the accurate synchronization of T and H$_2$O measurements at the 1 Hz timescale.
Figure 3. Distribution of the number of observations at $T \leq -40^\circ$C in the latitudinal and vertical view for the START08 and HIPPO campaigns. The color code shows the number of observations in each $10^\circ \times 25$ mb bin in the log scale.

Figure 4. PDFs of RHi for 1 Hz START08 and HIPPO#2-5 data. Different colors represent RHi of all data (red), the clear-sky (light grey) and the in-cloud data (dark grey). For all the 1 Hz data (red), the PDF of RHi $> 100\%$ follows an exponential decay: $\ln(\text{PDF}) = a + b \times \text{RHi}$, where $a = 5.4 \pm 0.5$, $b = -0.10 \pm 0.003$ ($\pm \sigma$, $\sigma$ is one standard deviation).
Figure 5. Distributions of 1 Hz RHi data at $T \leq -40^\circ$C for clear-sky (A) and in-cloud (B) conditions. The 1 Hz RHi data are color-coded by H$_2$O mixing ratio (ppmv). The black solid line and the grey dashed line represent water saturation line and homogeneous freezing line, respectively. Dark dashed line denotes 100% RHi.
Figure 6. Aircraft observation of ISSR. (A) An example of the aircraft observation time series of RHi (black line), H2O (blue line), T (red dotted line) and altitude (green line). The thick red line denotes RHi = 100%. The ISSR 1-D segment lengths (L_ISSR) and the spacings (L_spacing)
between the ISSRs are calculated by multiplying the true air speed with the transect time inside (or outside) the ISSRs. The minimum scales are ~230 m (1 second times 230 m/s mean true air speed). (B) Both ISSR segment length and spacing are binned by size between $2^i$ and $2^{i+1}$ (m), $i = 1, 2, 3...$ The abscissa shows mean $L_{\text{ISSR}}$ and $L_{\text{spacing}}$ values in each bin. The left ordinate shows the number of events of ISSR segment length ($N_{\text{ISSR}}$, red dots) and the number of events of ISSR spacing ($N_{\text{spacing}}$, green triangles) in each size bin. The right ordinate shows the mean $R\text{Hi}_{\max}$ value in each $L_{\text{ISSR}}$ bin (blue triangles). A power law fit is applied to the $N_{\text{ISSR}}$ versus $L_{\text{ISSR}}$, that is, $\log_{10}(N_{\text{ISSR}}) = a + b \times \log_{10}(L_{\text{ISSR}})$ (red dotted line). Similarly, a power law fit is applied to $N_{\text{spacing}}$ versus $L_{\text{spacing}}$, that is, $\log_{10}(N_{\text{spacing}}) = a + b \times \log_{10}(L_{\text{spacing}})$ (green dashed line). A linear fit is applied to $R\text{Hi}_{\max}$ versus the log scale $L_{\text{ISSR}}$, that is $R\text{Hi}_{\max} = a + b \times \log_{10}(L_{\text{ISSR}})$ (blue dotted line). For all linear fits in this study ± $\sigma$ means ± one standard deviation. Intercepts and slopes of the linear fits for all the graphs in this work are represented by values $a$ and $b$ in the legend, respectively.
A

ISSR condition inside vs. outside

\[ T_{\text{in}} < T_{\text{out}} \]
\[ H_2O_{\text{in}} > H_2O_{\text{out}} \]
Case 1: 72.7% 
(% of total ISSRs)

\[ T_{\text{in}} < T_{\text{out}} \]
\[ H_2O_{\text{in}} \leq H_2O_{\text{out}} \]
Case 2: 0.6%

\[ T_{\text{in}} \geq T_{\text{out}} \]
\[ H_2O_{\text{in}} > H_2O_{\text{out}} \]
Case 3: 26.7%

1-D Aircraft track

B

\[ a = 0.19 \pm 0.07 \]
\[ b = 0.88 \pm 0.006 \]
\[ a = -0.044 \pm 0.063 \]
\[ b = 0.090 \pm 0.005 \]

\[ 1 : 1 \]

C

\[ a = -0.0082 \pm 0.0124 \]
\[ b = 1.0 \pm 0.0001 \]
\[ a = 0.0070 \pm 0.0102 \]
\[ b = -0.00035 \pm 0.00012 \]

\[ 1 : 1 \]
Figure 7. Correlations between ISSR heterogeneities and T, H₂O horizontal heterogeneities. (A) ISSR locations are correlated with three cases of T and H₂O spatial heterogeneities. Grey and blank regions represent ISSRs and the adjacent horizontal (dP < 1 hPa) non-ISSRs, respectively. T_in and T_out represent the mean T value inside and outside (± 1 s) ISSRs, respectively; similarly for H₂O_in and H₂O_out. For 1094 horizontal ISSR segments, 99% of them correlate with higher H₂O heterogeneities (Cases 1+3) and 73% correlate with lower T heterogeneities (Cases 1+2). (B) dRHi_max is the difference between the RHi_max in each ISSR segment and the mean RHi of adjacent (± 1 s) non-ISSRs. The slope of dRHi_max (1:1 black line) is one, which is the linear combination of the fitted slope of T contribution (dRHi_T, red markers, slope: 0.090 ± 0.005) and the fitted slope of H₂O contribution (dRHi_q, blue markers, slope: 0.88 ± 0.006). (C) Similar to (B), but decompose the changes of H₂O partial pressure term (de, black 1:1 line) into the contributions from the changes in total pressure (de_P, red dots) and contributions from the changes of H₂O volume mixing ratio (de_H2OMR, blue dots). The slope of de is almost all contributed by the fitted slope of de_H2OMR.

Figure 8. Contributions from H₂O (dRHi_q, left ordinate) and T (dRHi_T, right ordinate) to dRHi_max using various scales of horizontally adjacent subsaturated air for comparison. dRHi_q and dRHi_T are in red dots and blue circles, respectively. Error bars represent one standard deviation of the linear fit for dRHi_q or dRHi_T. The large contributions from H₂O to dRHi hold for all length scales of adjacent subsaturated air from ~230 m to 6.7 km.
Figure 9. Contributions from H$_2$O ($d$RHi$_q$) and T ($d$RHi$_T$) to the $d$RHi$_{max}$ inside the ISSRs in the clear-sky (A) and in-cloud (B) conditions. The number of ISSRs in clear-sky (A) and cloudy (B) conditions are 783 and 273, respectively.

Figure 10. RH$_i$ horizontal variability in non-ISS (subsaturated + saturated) and ISS conditions. (A) 1 Hz $d$RH$_i$ analyses for non-ISS (sample size N = 269334); (B) 1 Hz $d$RH$_i$ analyses for ISS (N = 17834). The large contributions of H$_2$O horizontal variability to $d$RH$_i$ do not vary significantly between non-ISS and ISS conditions: 0.93 ± 0.0005 (non-ISS) and 0.94 ± 0.002 (ISS).
Figure 11. Contributions to RHi horizontal variability from H$_2$O and T horizontal variabilities. The horizontal variability ($dP < 1$ hPa) of all RHi at $T \leq -40$ °C is analyzed, including both ISS and non-ISS conditions. Intercept and slope of the linear fits (H$_2$O: blue dots, T: red dots) are represented by value a and b in the legend, respectively. (A) 1 Hz $dRHi$ for all RHi (sample size N = 288827); (B) 1 Hz $\sigma RHi$ at ~2.3 km (10 s) scale for all RHi (N = 57196); (C) scaling of H$_2$O and T contributions from ~230 m to 115 km (500 s). Sample sizes of $dRHi$ from ~230 m to 115 km are 288827, 85875, 20526, 6189, 1579, 372 and 166, respectively. Sample sizes of $\sigma RHi$ from ~690 m to 115 km are 192499, 57196, 18601, 5186, 1476, 768 and 303, respectively.
Figure 12. ISS observations along mixing lines in conservative tracer-tracer correlations. (A) O$_3$-CO correlations from START08 campaign. (B) Total water content and $\theta_q$ correlations in START08. The horizontal solid black line is the linear fit to the tropospheric branch of all RHi observations and dotted lines are the $\pm 3\sigma$ of the fits. For reference, grey background points in (A) and (B) show the observations in all T ranges. ISS data are colored by individual flight numbers with the same markers in (A) and (B). Because the mixing lines overlap with each other in (A) and (B), we highlighted a few straight mixing lines with arrows and colored flight numbers as examples (see arrows with labels in the figure).
Figure 13. Example of derivations of ISS spatial variability on a horizontal layer. The horizontal grey solid line denotes RHi = 100% and grey regions in (A) and (C) represent ISSRs. (A) Scheme 1 is an example of the horizontal distribution of RHi (black line), T (purple cross) and H2O (light blue dashed line) from the observation. (B) Scheme 2 either neglects H2O variability or T variability from the observation. The red short dashed line (blue long dashed line) uses the same T (H2O) variability as observed, but neglects H2O (T) fluctuations and only considers the mean H2O (T) value. The result gives no ISS when neglecting H2O fluctuations. (C) Scheme 3 uses T fluctuations to generate the same RHi distribution as observed, but still neglects H2O fluctuations. The result implies a lower T value in ISSRs (pink dashed line) than the observed T value (purple cross).