



AMERICAN METEOROLOGICAL SOCIETY

Monthly Weather Review

EARLY ONLINE RELEASE

This is a preliminary PDF of the author-produced manuscript that has been peer-reviewed and accepted for publication. Since it is being posted so soon after acceptance, it has not yet been copyedited, formatted, or processed by AMS Publications. This preliminary version of the manuscript may be downloaded, distributed, and cited, but please be aware that there will be visual differences and possibly some content differences between this version and the final published version.

The DOI for this manuscript is doi: 10.1175/MWR-D-16-0140.1

The final published version of this manuscript will replace the preliminary version at the above DOI once it is available.

If you would like to cite this EOR in a separate work, please use the following full citation:

Adams, D., H. Barbosa, and K. De los Rios, 2016: A spatiotemporal water vapor/deep convection correlation metric derived from the Amazon Dense GNSS Meteorological Network. *Mon. Wea. Rev.* doi:10.1175/MWR-D-16-0140.1, in press.



A spatiotemporal water vapor/deep convection correlation metric derived from the Amazon

Dense GNSS Meteorological Network

David K. Adams*

*Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Mexico City,
 Mexico*

Henrique M. J. Barbosa

Instituto de Física, Universidade de São Paulo, São Paulo, Brazil

Karen Patricia Gaitán De Los Ríos

*Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Mexico City,
 Mexico*

*Corresponding author address: Centro de Ciencias de la Atmósfera, Universidad Nacional
 Autónoma de México, Circuito Exterior s/n, Ciudad Universitaria, Del. Coyoacán 04510, México
 D.F..

E-mail: dave.k.adams@gmail.com

ABSTRACT

15 Deep atmospheric convection, which covers a large range of spatial scales
16 during its evolution, continues to be a challenge for models to replicate,
17 particularly over land in the Tropics. Specifically, the shallow-to-deep con-
18 vective transition and organization on the mesoscale are often not properly
19 represented in coarse resolution models. High resolution models offer in-
20 sights on physical mechanisms responsible for the shallow-to-deep transition.
21 Model verification, however, at both coarse and high resolution requires val-
22 idation and, hence, observational metrics which are lacking in the Tropics.
23 We provide here a straightforward metric derived from the Amazon Dense
24 GNSS Meteorological Network ($\sim 100\text{km} \times 100\text{km}$) based on a spatial cor-
25 relation decay timescale during convective evolution on the mesoscale. For
26 the shallow-to-deep transition, the correlation decay timescale is shown to be
27 around 3.5 hours. This novel result provides a much needed metric from the
28 deep tropics for numerical models to replicate.

29 1. Introduction

30 Deep precipitating convection dominates tropical meteorology and climate. Given the spatial
31 and temporal scales over which convection evolves and complex interactions with dynamic and
32 thermodynamic fields, it is a challenging phenomenon to reproduce in numerical models of all
33 resolutions. Coarse resolution models, where convection is parameterized, have had difficul-
34 ties replicating the continental diurnal convective cycle as well as convective organization on the
35 mesoscale (Bechtold et al. 2004; Grabowski et al. 2006; Folkins et al. 2014). Oftentimes, high-
36 resolution models have been utilized with the goal of ameliorating the continental (Tropics or Mid-
37 Latitudes) diurnal cycle or convective organization deficiencies through improvements in model
38 parameterizations (Rio et al. 2009; Rieck et al. 2014). However, high resolution modeling studies
39 (cloud-resolving models (CRM) to large-eddy simulation (LES)) have also been employed to infer
40 the actual physical mechanisms responsible for convective development/organization (e.g., cold
41 pools). The shallow-to-deep convective transition (s-t-d transition, for brevity), which coarser res-
42 olution models often fail to replicate, has received special attention. For example, modeling studies
43 have indicated that cold pool formation (Kuang and Bretherton 2006; Khairoutdinov and Randall
44 2006; Schlemmer and Hohenegger 2016), increasing cloud buoyancy (Wu et al. 2009), cumulus
45 congestus moistening (Waite and Khouider 2010) or large-scale vertical motions (Hohenegger and
46 Stevens 2013) control the s-t-d transition. Nevertheless, these mechanistic deductions from high
47 resolution models also require validation with high spatial-temporal resolution observations.

48 Ascertaining the physical realism of models with domain sizes on the order of 100km x 100km
49 requires corresponding mesoscale observations, which are typically lacking in the continental
50 Tropics. The Amazon Dense GNSS Meteorological Network (ADGMN) (Adams et al. 2015)
51 was created precisely to investigate mesoscale water vapor-convection interactions, specifically, to

52 examine the s-t-d transition and to test for responsible mechanisms. The ADGMN’s high tempo-
53 ral and spatial meteorological data lend themselves to metric creation to validate models, which
54 motivates this present study.

55 Although cloud top temperature (CTT) from satellite platforms can be used to evaluate cloud
56 evolution (e.g., (Hohenegger and Stevens 2013)), metrics based on GNSS (Global Navigational
57 Satellite Systems)/GPS (Global Positioning System) precipitable water vapor (PWV) are advan-
58 tageous for several reasons. Firstly, GNSS PWV frequency (≈ 5 minutes) provides sufficient tem-
59 poral resolution for rapidly developing cumulus fields. Moreover, GNSS PWV is all-weather
60 accurate, including cloudy and rainy conditions associated with deep convection. Furthermore,
61 PWV has a strong relationship with tropical convective precipitation and has served as the criti-
62 cal variable in numerous studies relating tropical convection to thermodynamics (Raymond 2000;
63 Bretherton et al. 2004; Lintner et al. 2011; Hottovy and Stechmann 2015; Schiro et al. 2016).
64 Finally, in models, PWV is a trivial variable to calculate unlike variables derived from cloud mi-
65 crophysical parameterizations.

66 Since mesoscale observationally based metrics are in short supply in the Tropics, we propose a
67 novel metric based on spatial cross correlations for gauging the mesoscale spatio-temporal evo-
68 lution of Amazonian convection. Similar to Adams et al. (2013), who used 3.5 years of GPS
69 PWV from the *Instituto Nacional de Pesquisas da Amazônia* (INPA) (see Figure 1) to derive a
70 “water vapor convergence” timescale, we also focus on the s-t-d transition. Adams et al. (2013)
71 inferred, based on the observed joint evolution of cloud fields and PWV, a characteristic s-t-d tran-
72 sition timescale of ~ 4 hours. Here, the temporal evolution of spatial correlation of PWV fields is
73 described with an exponential function, providing a spatial correlation decay timescale; a useful
74 diagnostic for models. In what follows, we describe the ADGMN, bring to light some ambiguities
75 associated with the definition of the s-t-d transition, and present the methodology for analyzing

76 spatial correlation decay timescales. Results focused on the seasonal and, particularly, the di-
77 urnal cycle are presented. Remarks on future studies with ADGMN data and expanding GNSS
78 meteorological networks in the Tropics conclude the paper.

79 **2. Context and motivation, study site, data and methodology**

80 *a. Context and motivation*

81 In its most generic form, the s-t-d transition can be idealized as the process of shallow cumulus,
82 growing into cumulus congestus, perhaps with showers, and finally morphing into deep precipi-
83 tating convective towers on typical timescales of 2 to 4 hours (Wu et al. 2009; Hohenegger and
84 Stevens 2013; Adams et al. 2013). However, perusal of the literature reveals rather varied, and
85 somewhat ambiguous, usage of the s-t-d transition concept, potentially leading to confusion. To
86 contextualize the present study and clarify the intended usage of our derived metric, we divide
87 s-t-d transition studies into three categories. These categories are neither exhaustive nor neces-
88 sarily mutually exclusive, though certainly nearly all studies could fit comfortably within one. The
89 first category, under which our study falls, follows Zehnder et al. (2006), Zhang and Klein (2010)
90 and Adams et al. (2013), all observationally based studies of continental convection. Here, a
91 fixed geographical area ($<50\text{km}$) is observed instrumentally, an Eulerian and decidedly mesoscale
92 perspective, as “individual” convective events develop over it. The temporal evolution of these
93 convective events are typically composited to derive transition timescales (Adams et al. 2013) or
94 evaluate thermodynamic or environmental conditions during the transition (Zehnder et al. 2006;
95 Zhang and Klein 2010). A second category, for which our metric is intended, involves high res-
96 olution models. These CRM and LES modeling studies ($\sim 100\text{km} \times 100\text{km}$) probe the complete
97 temporal evolution of deepening cumulus cloud fields over an entire spatial domain. Convective

cloud ensembles, during their different phases, provide domain-averaged variables for timescale analysis and/or for inferring physical controls on the s-t-d transition (e.g., cold pools, a critical lapse rate, congestus moistening, dynamical lifting) (Khairoutdinov and Randall 2006; Wu et al. 2009; Waite and Khouider 2010; Hohenegger and Stevens 2013) . Oftentimes, a single criteria such as domain/ensemble averaged cloud growth rate (Wu et al. 2009) is employed to signify that the transition has occurred. A third category, often couched or framed in the language of the s-t-d transition, could more accurately be described as suppressed versus convectively active conditions (Sahany et al. 2012; Hagos et al. 2014; Powell and Jr. 2015). This category of studies, both modelling (Kuang and Bretherton 2006) and observational (Xu and Rutledge 2016) are representative of much larger-scale circulations and their dynamic and thermodynamic conditions in which cumulus fields transition to deep convection. Their “shallow-to-deep transition” takes place on the order of days to greater than one week.

It should also be noted, however, that even the generic definition of three well-defined cumulus modes and their evolution may be overly idealized (Kumar et al. 2013). Consequently, we reserve some flexibility in defining the s-t-d transition, reflecting our approach and intent to create an easily reproducible metric. As noted above, we consider the time evolution of deep convective events at a single site concomitantly with surrounding water vapor fields. We do not discern the thermodynamic or dynamic conditions leading to the transition nor whether the convective event is associated with an already mature propagating mesoscale convective system. Nevertheless, since our metric is derived from CTT temporal evolution (“warm” $>280\text{K}$ shallow cumulus to “cold” $<235\text{K}$ deep cumulonimbus), this ensures some form of s-t-d transition is captured during our convective events (see Section 2d) .

b. Study site

The central Amazon, in and around Manaus (3.05S, 60.21W), represents a tropical rainforest climate with rainfall throughout the year, but with a notable minimum during July and August (Machado et al. 2004). There is a marked diurnal cycle; however, larger-scale synoptic forcing and/or long-lived mesoscale squall lines modulate the convective timing and intensity (Williams et al. 2002). Topographic relief is small ($\sim 150\text{m}$). Nevertheless, land-surface heterogeneity due to river-forest contrast generate favored zones of water vapor convergence (Adams et al. 2015) influencing precipitation timing and intensity (Fitzjarrald et al. 2008).

To derive metrics, long-term mesoscale observational studies of tropical convection are necessary. The mesoscale ADGMN ($\sim 100\text{km} \times 100\text{km}$) was created to study the complex interactions between water vapor and deep convection in a continental equatorial setting (Adams et al. 2015). The ADGMN (Figure 1) originally consisted of 10 sites, expanding to 21 sites during the last 8 months of the experiment ¹. Due to the inaccessible rainforest or seasonally flooded terrain surrounding Manaus, sites were concentrated in the urban zone. Nevertheless, the network spanned the subtle topographic effects, including elevated forest transition sites (EMBP, RDCK, RPDE, TRM3), low-lying rivers sites (CTLO, CMP1, CHR5, EMIR, HORT, MNCP, MNQI, PDAQ, TMB7), as well as a pristine rainforest station (ZF29). Mean station separation is 41km, the largest (MNCP-RPDE) is 131km and the smallest (INPA-CHR5), 3.3km. Station concentration in Manaus implies highly correlated PWV, which is considered in Section 2c.

¹The GOAM (GOAmazon) site created in anticipation of ARM Mobile Facility deployment (2014-15) had only 4 months of data and was excluded from the present analysis.

c. Data

Tropical water vapor observations capturing convective evolution are either too infrequent (e.g. radiosondes, polar-orbiting satellites), invalid or of questionable quality under cloudy/rainy conditions (e.g., vertically pointing microwave radiometers, satellite IR). Condensate and precipitation effects at GNSS microwave frequencies are small (Solheim et al. 1999) and the accuracy of GNSS PWV relative to radiosondes and radiometers (≈ 1 to 2 mm) has been well-established (Bevis et al. 1992; Rocken et al. 1993). Even in the high humidity, logistically challenging environment of the Amazon, GNSS PWV is accurate (Sapucci et al. 2007; Adams et al. 2011a,b, 2015). The GNSS PWV observation cone (radius ~ 10 km) and ADGMN site distribution permit capturing PWV field evolution from the cumulus stage to cumulonimbus lines or clusters.

For the 21 stations, GNSS PWV was estimated every 5 minutes with GIPSY-OASIS (GPS-Inferred Positioning System and Orbit Analysis Simulation Software), utilizing geodetic-grade receivers and antennas and surface pressure and temperature from colocated meteorological sensors. Where meteorological sensors failed or did not exist (only NAUS site) pressure, using the hypsometric equation, and temperature were interpolated from the nearest station. The region's homogeneous temperature fields and flat topography ensure this interpolation has negligible effects on PWV.

To identify deep convective events, INPA surface precipitation as well as GOES 12 ($10.7\mu m$) satellite data were employed. Since INPA failed at the end of 2011, Tropical Rainfall Measuring Mission (TRMM) 3B42 (3 hour precipitation rate) from the 25 km x 25 km pixel centered over CHR5, the closest station, was used. GOES 12 IR brightness temperature; i.e., CCT, was calculated as the average of the 4 x 4 pixels (16 km x 16 km) corresponding to the GNSS cone of observation centered over INPA (2011) and over CHR5 (2012).

163 *d. Methodology*

164 For calculating correlation decay timescales during the mesoscale evolution to deep convection,
165 the convective events were identified essentially following Adams et al. (2013). A deep convective
166 event was defined as reporting precipitation and, minimally, a 50K fall in CTT in less than 2
167 hours to 235K or below. This definition results in minimizing misidentification of stratiform and
168 showery congestus precipitation as deep convective precipitation as well as ensuring that a shallow
169 cumulus stage is observed. Likewise, these strong CTT drops were associated with large upswings
170 in PWV, the peak of which was utilized as the temporal identifier of the convective event origin
171 (i.e., $t = 0$). The time series of the correlation vs distance slope, based on each time bin, was then
172 extended backwards 14 hours prior to time of maximum PWV, as in Adams et al. (2013). This
173 implies covering the entire diurnal cycle, though here we focus solely on the last 6 hours, which
174 contains the s-t-d transition. Over the one-year period of study, 118 days reported some form of
175 precipitation; however, only 67 deep convective events met these more stringent criteria.

176 To quantify the spatiotemporal evolution of PWV, cross correlations between stations were cal-
177 culated in 30 minute and 1 hour bins. Each time bin correlation was calculated from $t = 0$ h (i.e.,
178 convective event occurrence) every hour or every 30 minutes. For example, in the first hour with
179 respect to convective event occurrence; that is, between $t = 0$ h and $t = -1$ h, there are 12 five-
180 minute PWV values for each individual event. Given 67 convective events, this would then imply
181 a maximum of $12 \times 67 = 804$ data points within that 1 hour time bin to be correlated with the
182 corresponding $t = 0$ h to $t = -1$ h data points from a different station. This is then carried out for
183 every time bin, $t = -1$ h to $t = -2$ h,..., up to $t = -13$ h to $t = -14$ h. With up to 20 other stations available
184 for cross correlation in the corresponding 1 hour time bin, as many as 231 correlation coefficients
185 enter into the calculation of the separation distance versus correlation coefficient. In this way, the

slope of correlation coefficient versus distance, for each 1 hour bin, was estimated (significant to the 95th percentile) from the fitted regression line fixed at correlation coefficient $R = 1$ at distance $x = 0$ (see Figure 2). The change in slope of these fitted regression lines, as a function of time, is then evaluated. The resulting temporal evolution of spatial correlation is described by a simple functional form from which a time decay constant is derived, thereby providing an easily replicable metric.

Taking into account the network's irregular geographical configuration, the time evolution of the cross correlations was checked for sensitivity to this spatial distribution in two ways. Firstly, as a direct approach, 5 closely spaced and centrally located stations (PDAQ, PNT8, RDCK, INPA, and NAUS) were removed and the calculations repeated. The average station separation distance rose from 41km to 53km, diminishing the influence of these highly correlated stations. Secondly, we implemented a Monte Carlo approach in which one station was randomly removed and the data resampled. The correlation slope with distance for each time bin was recalculated for 100 trials. The time constant from the fitted function and its associated uncertainties were evaluated for the 100 trials, and this was performed as 2 through 18 stations were removed (see Section 3).

Considering that varying conditions (e.g., surface forcing or free tropospheric thermodynamic structure) may influence the correlation decay timescale, drier (July-December) versus wet season (January-April), as well as the diurnal cycle of convection, were examined. We provide more details on the latter in Section 3, given that the continental diurnal cycle and specifically from the Amazon Region (Betts and Jakob 2002a,b; Grabowski et al. 2006), among many others) underpins much of the original s-t-d transition research; this in addition to our goal of providing an easily replicable metric.

3. Results and Discussion

The 67 convective events occurred mostly following the diurnal cycle (55 events) with two-thirds occurring between 12pm and 6pm local time (44 events). “Nocturnal” convection (8pm to 12pm local time) consisted of only 12 events. For the purpose of seasonal comparison, the wet season consisted of 24 events while the drier seasons consisted of 27 without consideration for the time of occurrence. The 16 events occurring between April and July 2011 were not included in the seasonal comparison since only 10 GNSS meteorological sites existed at that time.

Figure 2 displays the correlation coefficient as a function of distance for one hour time bins over the 67 convective events. For visual clarity, and to focus on the s-t-d transition, only the 6 hours prior ($t = -6\text{h}$ to $t = 0$) to the convective event are displayed. This figure represents the time evolution of spatial correlations; that is, the change in angle between the slopes for each time bin represents the temporal evolution of spatial decorrelation. The lines fitted to the correlation versus station separation distance are fixed to $R = 1$ at $x = 0$. Although scatter is large, the slopes calculated are all statistically significant (95th percentile). As one considers progressively earlier times before the development of convective activity (prior to $t = -6\text{h}$), the fitted lines fall closely one upon the other (not shown), and correlation decays only slightly (~ 0.15) over the maximum separation distance of the network. Within $t = 0\text{h}$, correlation decays rapidly to ~ 0.5 at the limit of separation distance ($\sim 150\text{km}$). When these slopes are expressed as a function of time, the functional form becomes apparent (Figure 3). From the analysis of these 67 events, there is a non-linear decay in correlation beginning around $t = -4\text{h}$ and only a weaker quasi-linear decay back to $t = -12\text{h}$ (Figure 3). In this figure, both 1 hour and 30 minute bins data are plotted making clear that this temporal binning is unimportant. The error bars represent the 95th percentile range for

the correlation vs distance coefficients used to derived the slope (i.e., the lines in Figure 2). Fitted with an exponential function, a correlation decay timescale of ~ 3.5 hours is revealed.

Solely for visualization purposes, PWV anomaly fields from $t = -5\text{h}$ to $t = 0\text{h}$ are shown in Figure 4. Anomalies were calculated by subtracting the average (over all stations and all times) from the 1 hour bin average of the 67 events at each site. Cressman interpolation analysis was utilized for plotting; the plots being fairly insensitive to the radius of influence chosen. The PWV anomaly fields are fairly flat from $t = -5\text{h}$ to $t = -4\text{h}$. Commencing at $t = -3\text{h}$, the water vapor fields become more structured, maximizing the PWV anomaly gradient, and concentrating the positive PWV anomalies (i.e., a proxy for water vapor convergence) in the central portion of the network. Given that the initiation of deep convection is associated with the largest positive PWV anomalies at INPA (2011) and CHR5 (2012), a maximum positive PWV anomaly centered near INPA, or nearby, should be expected. Similar results are obtained, not surprisingly, for CTT as shown in the example for the 55 diurnal convective events in Figure 7.

To test the decay timescale robustness, data denial analyses were carried out. In the first case, the 5 clustered stations noted in Section (2c) were removed directly and statistics recalculated. The results are essentially identical with mean $\tau = 3.45$ hours and $\sigma = 0.362$ hours. For the Monte Carlo random data denial analysis, the elimination of 10 sites produces a mean difference of -0.1h and an increase in σ of 0.21 to $\sigma = 0.57$ hours, indicating minimal influence of the station distribution.

Decay timescale sensitivity to environmental conditions was gauged through analysis of wet season versus the dry and dry-to-wet transition season as well as diurnal versus nocturnal convective events (Figure 5 and 6). Thermodynamic conditions, in particular stability measures, (e.g., CAPE, CIN) as well as the water vapor distribution vary seasonally in the Amazon, influencing the intensity and frequency of convection (Fu et al. 1999; Li and Fu 2004). The dry and dry-to-wet transi-

254 tion experience less frequent, but often more intense convection (Williams et al. 2002). During the
 255 wet season, precipitating convection is frequent and the free troposphere approaches a moist adia-
 256 bat tied to the sub-cloud layer, thereby limiting both CAPE and CIN, but increasing precipitation
 257 efficiency (Machado et al. 2004). Figure 5 contains a comparison of decay timescales associated
 258 with the 24 wet and 27 dry/dry-to-wet season convective events. The wet season demonstrates
 259 much greater heterogeneity, with larger decreases in spatial correlations compared to dry/dry-
 260 to-wet seasons. Visual inspection of GOES CTT animations also show wider-spread cumulus
 261 convection typically deepening and organizing over different portions of the network during the
 262 wet season. Though wet-seasons spatial correlation scales are much smaller, the decay timescale
 263 are essentially the same; $\tau = 2.72\text{h}$ (wet) and $\tau = 3.02\text{h}$ (dry/dry-to-wet).

264 Considering that the continental tropical diurnal cycle has strongly motivated the research of
 265 the s-t-d transition, we have examined diurnal vs nocturnal convection. From Figure 6, the decay
 266 timescale increases by approximately one hour, $\tau = 2.83\text{h}$ (Diurnal) and $\tau = 3.96\text{h}$ (Nocturnal).
 267 The nocturnal evolution deviates strongly from the exponential fit around $t = -8\text{h}$ to $t = -6\text{h}$, but
 268 still displays the correlation drop off during the s-t-d transition; that is, the last 4 hours prior to
 269 deep convection (Adams et al. 2013). Examination of GOES CTT animations reveals no obvious
 270 deviating behavior 8 to 6 hours prior to $t = 0$ for these nocturnal events. Nonetheless, with only
 271 12 events, these statistics are certainly less reliable. To confirm that the s-t-d transition, as most
 272 commonly studied, is occurring, composites of CTT were also created for the diurnal convective
 273 events. In Figure 7, the composite CTT fields of the 55 diurnal event is presented. Prior to $t = -3\text{h}$,
 274 the CTT fields are homogeneous. Between $t = -3\text{h}$ and the convective event ($t = 0$), cloud fields
 275 begin to deepen rapidly (i.e., the s-t-d transition).

276 The decay timescale derived from the above analysis is consistent with the 4-hour water vapor
 277 convergence timescale for the Amazon s-t-d transition (Adams et al. 2013). This provides for

278 a physical interpretation. Consider the simplest case of the 55 diurnal convective events. The
 279 10km radius GPS cone of view observes cumulus clouds interspersed with clear sky during the
 280 shallow phase. With solar insolation, convective boundary layer deepening and cumulus cloud
 281 growth result in $d(\text{PWV})/dt > 0$ (a proxy for wv convergence in the atmospheric column). At this
 282 stage, all sites in the network essentially behave the same and PWV time evolution is correlated
 283 over greater distances. As congestus clouds grow, convergence zones begin to narrow. Figures
 284 5 and 6 of Khairoutdinov and Randall (2006) provide a nice visualization of this process (which
 285 they attribute to cold pool collisions). Simultaneously, wv convergence weakens over the “non-
 286 congestus regions” and spatial decorrelation increases. Finally, growth into deep cumulonimbus
 287 towers, lines and clusters with stronger vertical accelerations confines the zones of augmenting
 288 $d(\text{PWV})/dt > 0$ even more so, and the rest of the network experiences much weaker, zero wv
 289 vapor convergence or perhaps even divergence. This deep convective stage further accelerates
 290 the decorrelation. Examining Figures 4 and 7, one can idealize the decorrelation length scale as
 291 the inverse of the probability of a station lying within the same contours as other stations. This
 292 probability decreases as t approaches 0h; i.e., more contours on the figures. The spatial structuring
 293 (i.e., decreased correlation length) and intensity of water vapor convergence are thus intrinsically
 294 tied together and, hence, is a useful gauge of the s-t-d transition . One could certainly speculate that
 295 growth into mesoscale convective systems again increases PWV correlation length given induced
 296 mesoscale circulations and associated water vapor convergence fields, but this will be investigated
 297 in another study.

298 **4. Conclusions and future work**

299 This derived correlation decay timescale is agnostic with respect to any of the putative phys-
 300 ical mechanisms responsible for the s-t-d transition. Nevertheless, for at least the case of con-

301 tinent tropical convection, high resolution models making mechanistic deductions with respect
302 to convective evolution can now attempt to replicate this metric. In future work, ADGMN data
303 will be employed to examine the possible role of cold pools in the s-t-d transition, correlating
304 their occurrence with the increase in water vapor convergence and observed cloud growth. For-
305 tunately, in recent years, GNSS/GPS meteorology has expanded into tropical regions, COCONet
306 in the Caribbean and TLALOCNet in Mexico. The large-scale networks provide many anchor
307 sites around which mesoscale dense network can be created in varying topographic and climatic
308 settings.

309 *Acknowledgments.* We thank Ben Lintner and Yolande Serra for their comments on the
310 manuscript. We also thank Alain Protat and two anonymous reviewers for their constructive criti-
311 cisms. Financial support for the ADGMN came through Cooperation Project 0050.0045370.08.4
312 between PETROBRAS and INPE (Brazil) and from the INPA/LBA (Brazil) (Principle Investiga-
313 tor Icaro Vitorello). H.B. acknowledges the financial support of FAPESP grant 2013/50510-5.
314 Financial support for this paper was also provided by UNAM PAPIIT IA100916. We also thank
315 the students of the graduate program Clima e Ambiente (UEA/INPA) for their contributions. Data
316 are available upon request from the corresponding author.

317 **References**

- 318 Adams, D. K., R. M. S. Fernandes, and J. M. F. Maia, 2011a: GNSS Precipitable Water Vapor
319 from an Amazonian Rain Forest Flux Tower. *Journal of Atmospheric and Oceanic Technology*,
320 **28**, 1192–1198.
- 321 Adams, D. K., S. I. Gutman, K. L. Holub, and D. S. Pereira, 2013: GNSS observations of deep
322 convective time scales in the Amazon. *Geophys. Res. Lett.*, **40**, 2818–2823.

- 323 Adams, D. K., and Coauthors, 2011b: A Dense GNSS Meteorological network for observing deep
324 convection in the Amazon. *Atmos. Sci. Let.*, **12**, 207–212, doi:10.1002/asl.312.
- 325 Adams, D. K., and Coauthors, 2015: The Amazon Dense GNSS Meteorological Network: A new
326 approach for examining water vapor and deep convection interactions in the Tropics. *Bulletin of*
327 *the American Meteorological Society*, **96 (12)**, 2151–2165.
- 328 Bechtold, P., J. Chaboureau, A. Beljaars, A. Betts, M. Kohler, M. Miller, and J. Redelsperger,
329 2004: The simulation of the diurnal cycle of convective precipitation over land in a global
330 model. *Quart. J. Roy. Meteor. Soc.*, **130**, 3119–3137.
- 331 Betts, A. K., and C. Jakob, 2002a: Evaluation of the diurnal cycle of precipitation, surface ther-
332 modynamics, and surface fluxes in the ECMWF model using LBA data. *J. Geophys Res.*, **107**,
333 doi:10.1029/2001JD000427.
- 334 Betts, A. K., and C. Jakob, 2002b: Study of diurnal convective precipitation over Amazonia using
335 a single column model. *J. Geophys Res.*, **107**, doi:10.1029/2001JD002264.
- 336 Bevis, M., S. Businger, T. A. Herring, C. Rocken, R. Anthes, and R. H. Ware, 1992: GPS mete-
337 orology: Sensing of atmospheric water vapor using the Global Positioning System. *J. Geophys*
338 *Res.*, **97**, 15 787–15 801.
- 339 Bretherton, C. S., M. E. Peters, and L. E. Back, 2004: Relationships between water vapor path and
340 precipitation over the tropical oceans. *Journal of Climate*, **17**, 1517–1528.
- 341 Fitzjarrald, D. R., R. K. Sakai, O. L. L. Moraes, R. C. de Oliveira, O. C. Acevedo, M. J. Czikowsky,
342 and T. Beldini, 2008: Spatial and temporal rainfall variability near the Amazon-Tapajós conflu-
343 ence. *J. Geophys Res.*, **113**, doi:10.1029/2007JG000596.

344 Folkins, I., T. Mitovski, and J. R. Pierce, 2014: A simple way to improve the diurnal cycle in con-
 345 vective rainfall over land in climate models. *J. Geophys Res.*, **119**, doi:10.1002/2013JD020149.

346 Fu, R., B. Zhu, and R. E. Dickinson, 1999: How do atmosphere and land surface influence seasonal
 347 changes of convection in the tropical Amazon? *Journal of Climate*, **12**, 1306–1321.

348 Grabowski, W. W., and Coauthors, 2006: Daytime convective development over land: A model
 349 intercomparison based on LBA observations. *Quart. J. Roy. Meteor. Soc.*, **132**, 317–344.

350 Hagos, S., Z. Feng, K. Landu, and C. N. Long, 2014: Advection, moistening, and shallow-to-
 351 deep convection transitions during the initiation and propagation of Madden-Julian Oscillation.
 352 *J. Adv. Model. Earth Syst.*, **6**, 938–949.

353 Hohenegger, C., and B. Stevens, 2013: Preconditioning deep convection with cumulus convection.
 354 *J. Atmos. Sci.*, **70**, 448–464.

355 Hottovy, S., and S. N. Stechmann, 2015: A spatiotemporal stochastic model for tropical precipita-
 356 tion and water vapor dynamics. *Journal of the Atmospheric Sciences*, **72**, 4721–4738.

357 Khairoutdinov, M., and D. Randall, 2006: High-resolution simulation of shallow-to-deep convec-
 358 tion transition over land. *J. Atmos. Sci.*, **63**, 3421–3436.

359 Kuang, Z., and C. S. Bretherton, 2006: A mass-flux scheme view of a high-resolution simulation
 360 of a transition from shallow to deep cumulus convection. *J. Atmos. Sci.*, **63**, 1895–1909.

361 Kumar, V., C. Jakob, A. Protat, P. T. May, and L. Davies, 2013: The four cumulus cloud modes and
 362 their progression during rainfall events: A C-band polarimetric radar perspective. *J. Geophys.*
 363 *Res.*, **118**, 83758389.

Li, W., and R. Fu, 2004: Transition of the large-scale atmospheric and land surface conditions from the dry to the wet season over Amazonia as diagnosed by the ecmwf re-analysis. *Journal of Climate*, **17**, 2637–2651.

Lintner, B. R., C. E. Holloway, and J. D. Neelin, 2011: Column water vapor statistics and their relationship to deep convection, vertical and horizontal circulation, and moisture structure at nauru. *Journal of Climate*, **24** (20), 5454–5466, doi:10.1175/JCLI-D-10-05015.1.

Machado, L. A. T., H. Laurent, N. Dessay, and I. Miranda, 2004: Seasonal and diurnal variability of convection over the Amazonia: A comparison of different vegetation types and large scale forcing. *Theor. Appl. Climatol.*, **78**, 61–77, doi:0.1007/s00704-004-0044-9.

Powell, S. W., and R. A. H. Jr., 2015: Evolution of precipitation and convective echo top heights observed by TRMM radar over the indian ocean during dynamo. *J. Geophys. Res.*, **120**, 3906–3919.

Raymond, D., 2000: Thermodynamic control of tropical rainfall. *Quart. J. Roy. Meteor. Soc.*, **126**, 889–898.

Rieck, M., C. Hohenegger, and C. C. van Heerwaarden, 2014: The influence of land surface heterogeneities on cloud size development. *Monthly Weather Review*, **142** (10), 3830–3846, doi:10.1175/MWR-D-13-00354.1.

Rio, C., F. Hourdin, J.-Y. Grandpeix, and J.-P. Lafore, 2009: Shifting the diurnal cycle of parameterized deep convection over land. *Geophys. Res. Lett.*, **36**, doi:10.1029/2008GL036779.

Rocken, C., R. H. Ware, T. V. Hove, F. Solheim, C. Alber, J. Johnson, M. Bevis, and S. Businger, 1993: Sensing atmospheric water vapor with the Global Positioning System. *Geophys. Res. Lett.*, **20**, 2631–2634.

386 Sahany, S., J. D. Neelin, K. Hales, and R. B. Neale, 2012: Temperaturemoisture dependence of
 387 the deep convective transition as a constraint on entrainment in climate models. *Journal of the*
 388 *Atmospheric Sciences*, **69** (4), 1340–1358.

389 Sapucci, L. F., L. A. T. Machado, J. F. G. Monico, and A. Plana-Fattori, 2007: Intercomparison
 390 of integrated water vapor estimates from multisensors in the Amazonian region. *Journal of*
 391 *Atmospheric and Oceanic Technology*, **24**, 1880–1894.

392 Schiro, K. A., J. D. Neelin, D. K. Adams, and B. R. Lintner, 2016: Deep convection and
 393 column water vapor over tropical land vs. tropical ocean: A comparison between the Ama-
 394 zon and the Tropical Western Pacific. *Journal of the Atmospheric Sciences*, in press, doi:
 395 10.1175/JAS-D-16-0119.1.

396 Schlemmer, L., and C. Hohenegger, 2016: Modifications of the atmospheric moisture field as a
 397 result of cold-pool dynamics. *Quart. J. Roy. Meteor. Soc.*, **142**, 30–42.

398 Solheim, F., J. Vivekanandan, R. H. Ware, and C. Rocken, 1999: Propagation delays induced in
 399 gps signals by dry air, water vapor, hydrometeors, and other particulates. *J. Geophys. Res.*, **104**,
 400 9663–9670.

401 Waite, M. L., and B. Khouider, 2010: The deepening of tropical convection by congestus precon-
 402 ditioning. *J. Atmos. Sci.*, **67**, 2601–2615.

403 Williams, E., and Coauthors, 2002: Contrasting convective regimes over the Amazon: Implica-
 404 tions for cloud electrification. *J. Geophys Res.*, **107**, 8082–8101.

405 Wu, C.-M., B. Stevens, and A. Arakawa, 2009: What controls the transition from shallow to deep
 406 convection? *J. Atmos. Sci.*, **66**, 1793–1806.

- 407 Xu, W., and S. Rutledge, 2016: Time scales of shallow-to-deep convective transition associated
408 with the onset of Madden-Julian Oscillations. *Geophys. Res. Lett.*, **6**, 2880–2888.
- 409 Zehnder, J., L. Zhang, D. Hansford, A. Radzan, N. Selover, and C. Brown, 2006: Using digital
410 cloud photogrammetry to characterize the onset and transition from shallow to deep convection
411 over orography. *Mon. Wea. Rev.*, **134**, 2527–2546.
- 412 Zhang, Y., and S. A. Klein, 2010: Mechanisms affecting the transition from shallow to deep
413 convection over land: Inferences from observations of the diurnal cycle collected at the ARM
414 Southern Great Plains Site. *Journal of the Atmospheric Sciences*, **67**, 2943–2959.

415	LIST OF FIGURES	
416	Fig. 1.	Map of the Manaus Dense GNSS Meteorological Network from April 2011 to April 2012. The color scheme represents the frequency of PWV data (11256 total data values) for the 67 convective events used in this study. GOAM data were not utilized. PDAQ failed in October and was not utilized in the PWV anomaly plot (Figure 4), but was used in correlation vs distance statistics to better assess the data-denial tests. 21
417		
418		
419		
420		
421	Fig. 2.	Scatterplot of correlation vs separation distance as a function of different one-hour time bins, between $t = 0h$ and $t = -6h$ for the 67 events. The slope of the fitted lines is statistically significant at the 95th percentile. 22
422		
423		
424	Fig. 3.	Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for 67 convective events. Both 1 hour (blue lines and circles) and 30 minute (red line and x symbols) time bins are included for comparison purposes. Functional form, average decay timescale, τ and 95th percentile confidence intervals are shown. 23
425		
426		
427		
428	Fig. 4.	Plot of PWV anomalies (mm) fields calculated from average of 67 convective events for 5 hours before convective events. 24
429		
430	Fig. 5.	Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for wet (red, 24 events) versus dry and dry-to-wet season (blue, 27 events). The 16 events occurring during the wet-to-dry transition are not included. 25
431		
432		
433	Fig. 6.	Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for diurnal (55 events, red) versus nighttime (12 events, blue). 26
434		
435	Fig. 7.	Plot of the temporal evolution ($t = -5h$ to $t = 0h$) of GOES cloud top temperature (K) fields calculated for 55 diurnal convective events. 27
436		

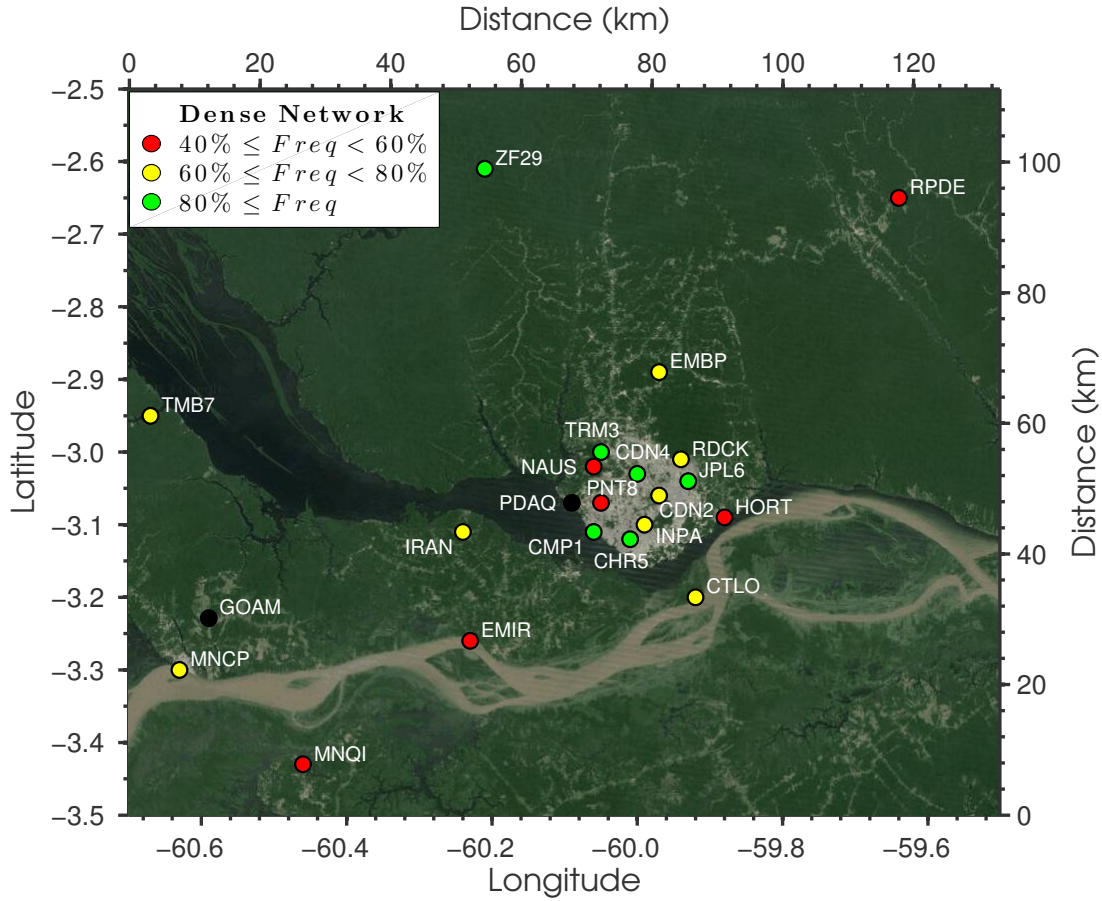


FIG. 1. Map of the Manaus Dense GNSS Meteorological Network from April 2011 to April 2012. The color scheme represents the frequency of PWV data (11256 total data values) for the 67 convective events used in this study. GOAM data were not utilized. PDAQ failed in October and was not utilized in the PWV anomaly plot (Figure 4), but was used in correlation vs distance statistics to better assess the data-denial tests.

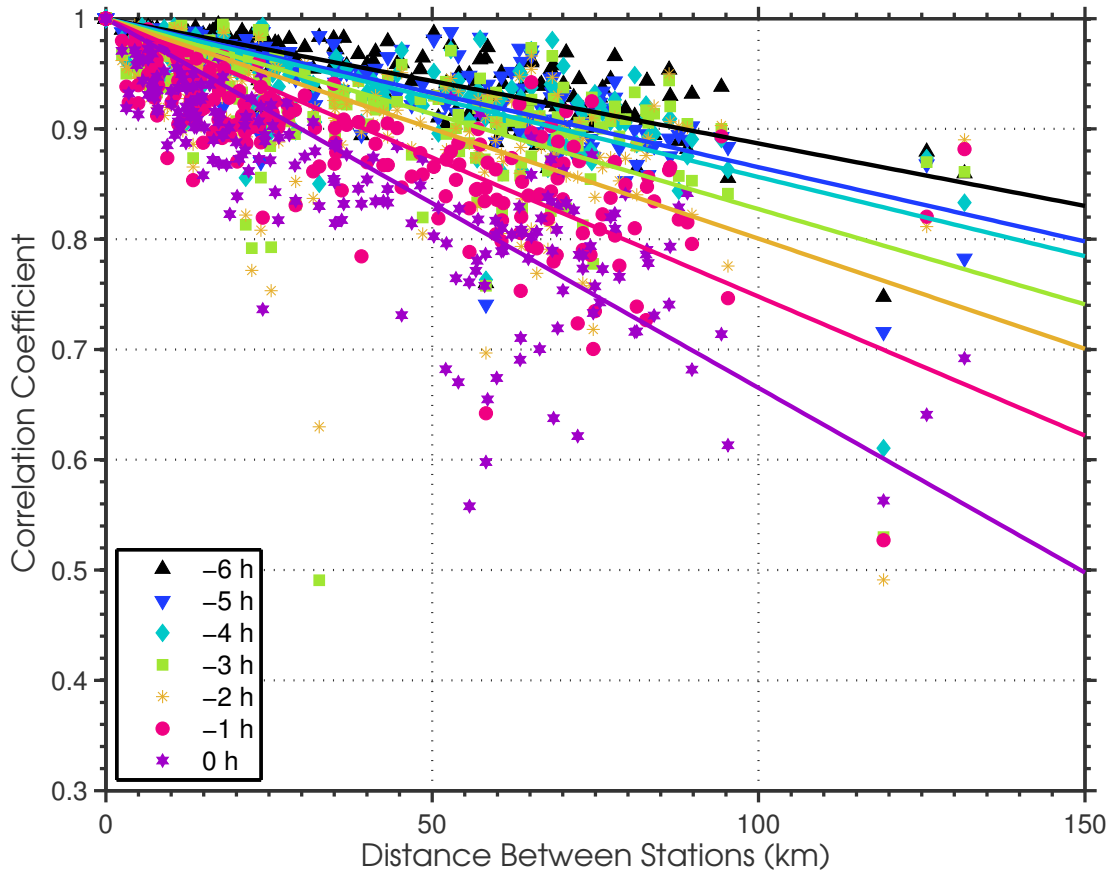


FIG. 2. Scatterplot of correlation vs separation distance as a function of different one-hour time bins, between $t = 0h$ and $t = -6h$ for the 67 events. The slope of the fitted lines is statistically significant at the 95th percentile.

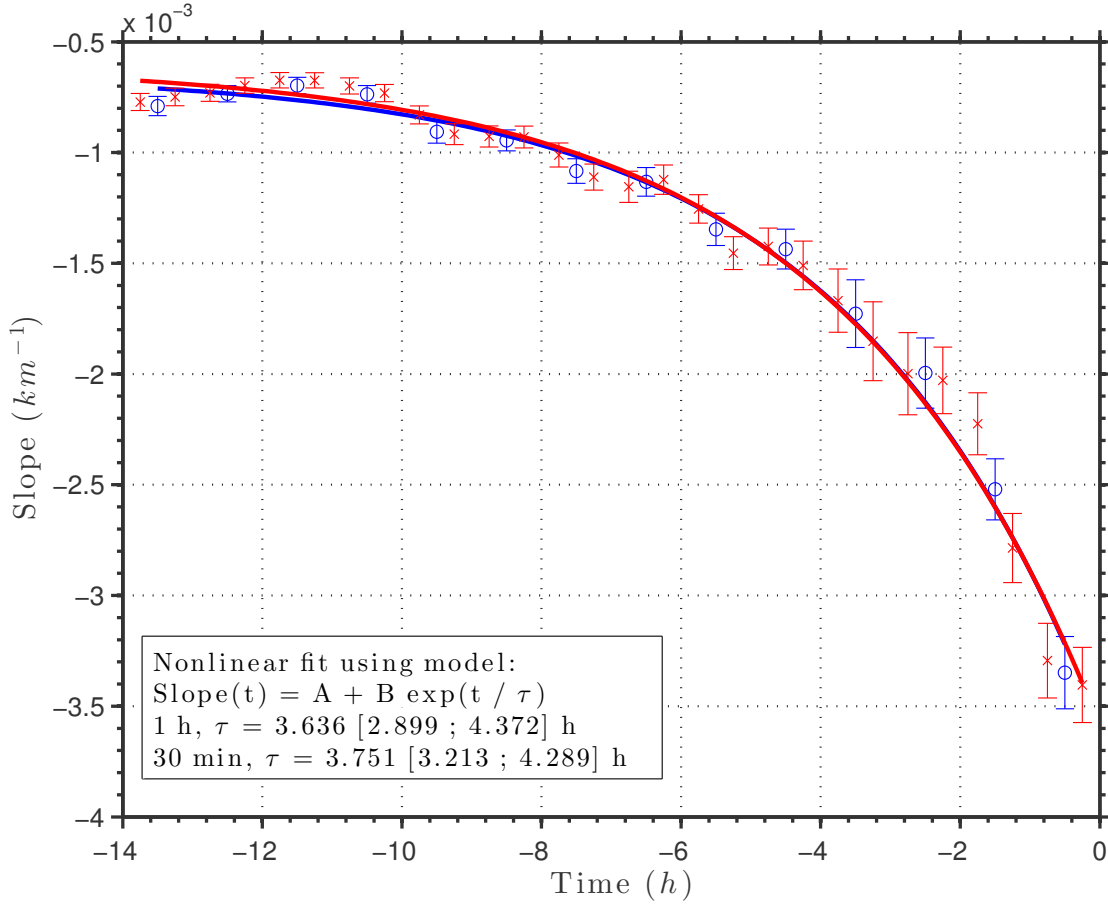
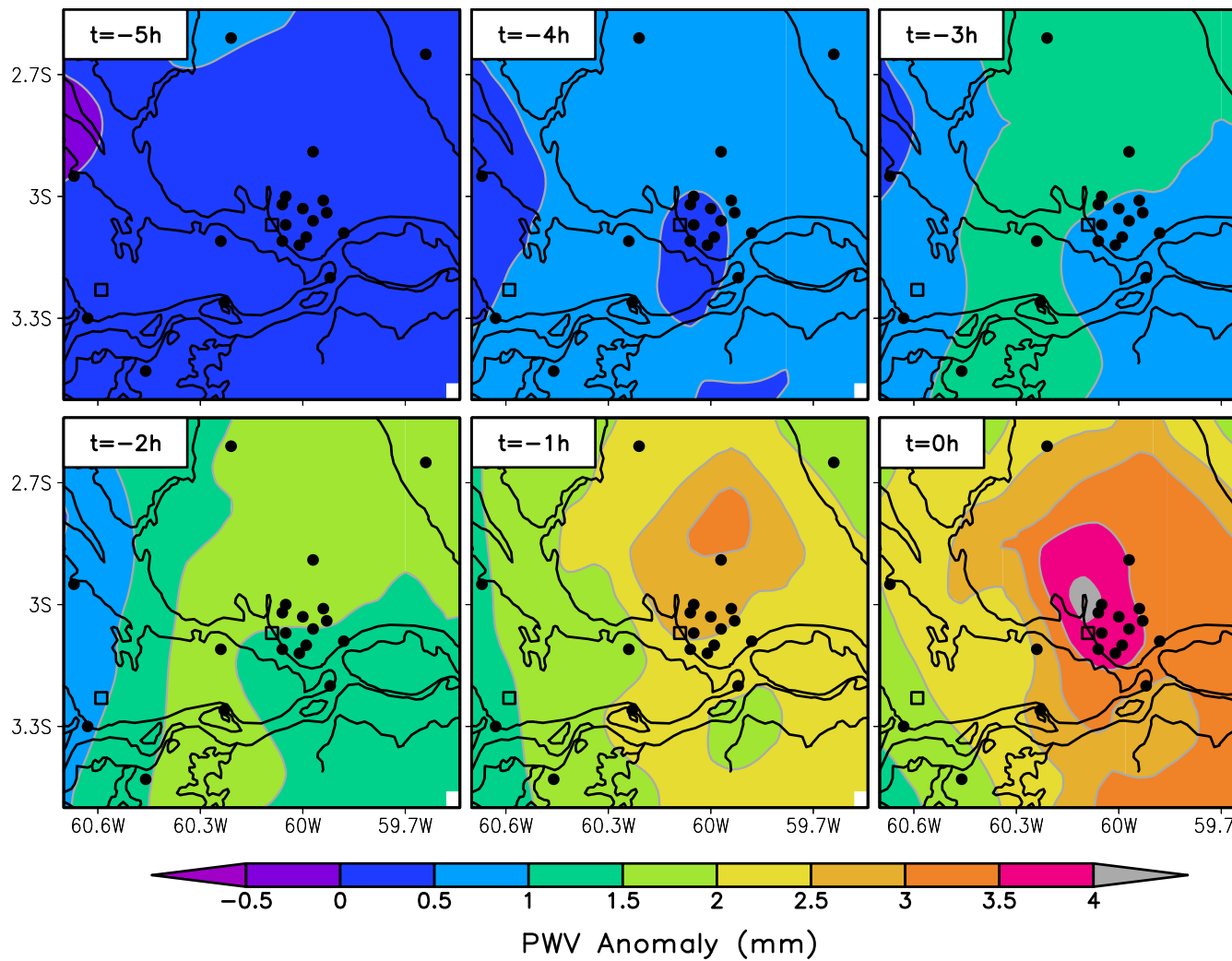


FIG. 3. Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for 67 convective events. Both 1 hour (blue lines and circles) and 30 minute (red line and x symbols) time bins are included for comparison purposes. Functional form, average decay timescale, τ and 95th percentile confidence intervals are shown.



447 FIG. 4. Plot of PWV anomalies (mm) fields calculated from average of 67 convective events for 5 hours before
 448 convective events.

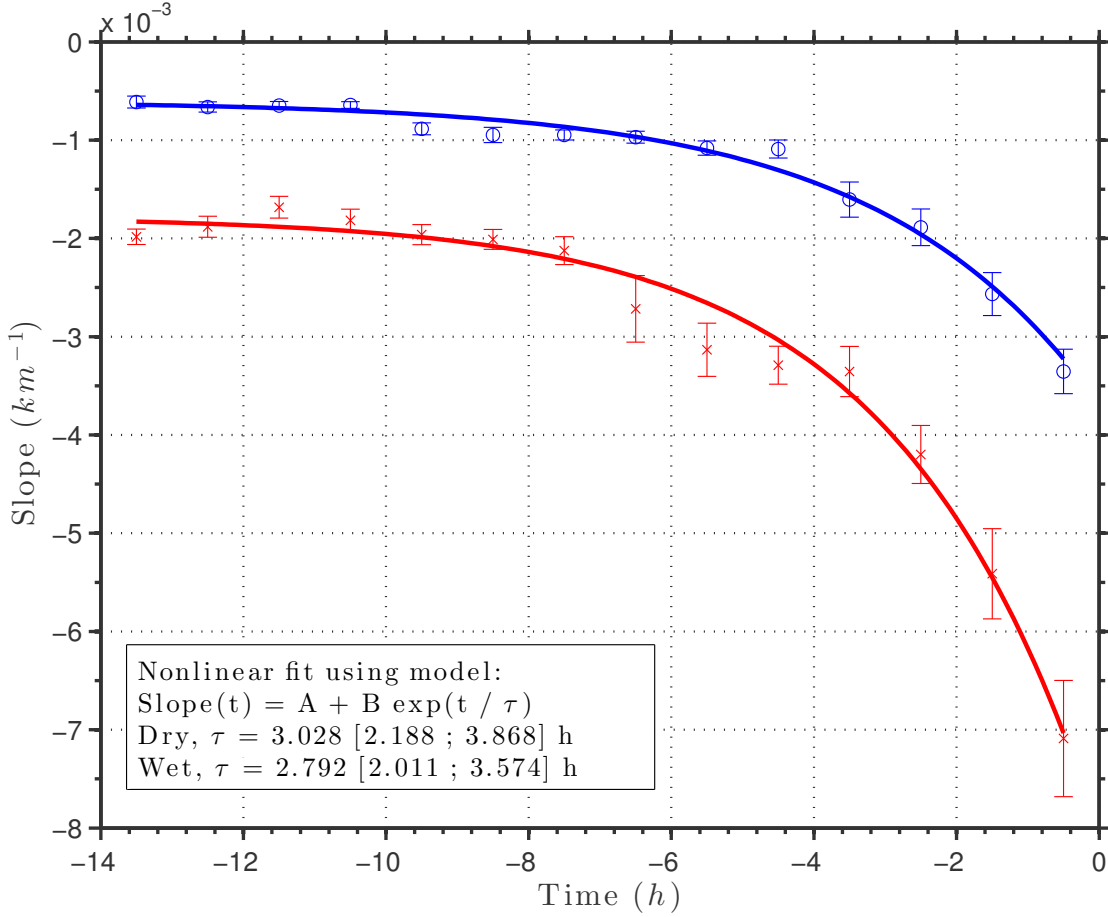


FIG. 5. Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for wet (red, 24 events) versus dry and dry-to-wet season (blue, 27 events). The 16 events occurring during the wet-to-dry transition are not included.

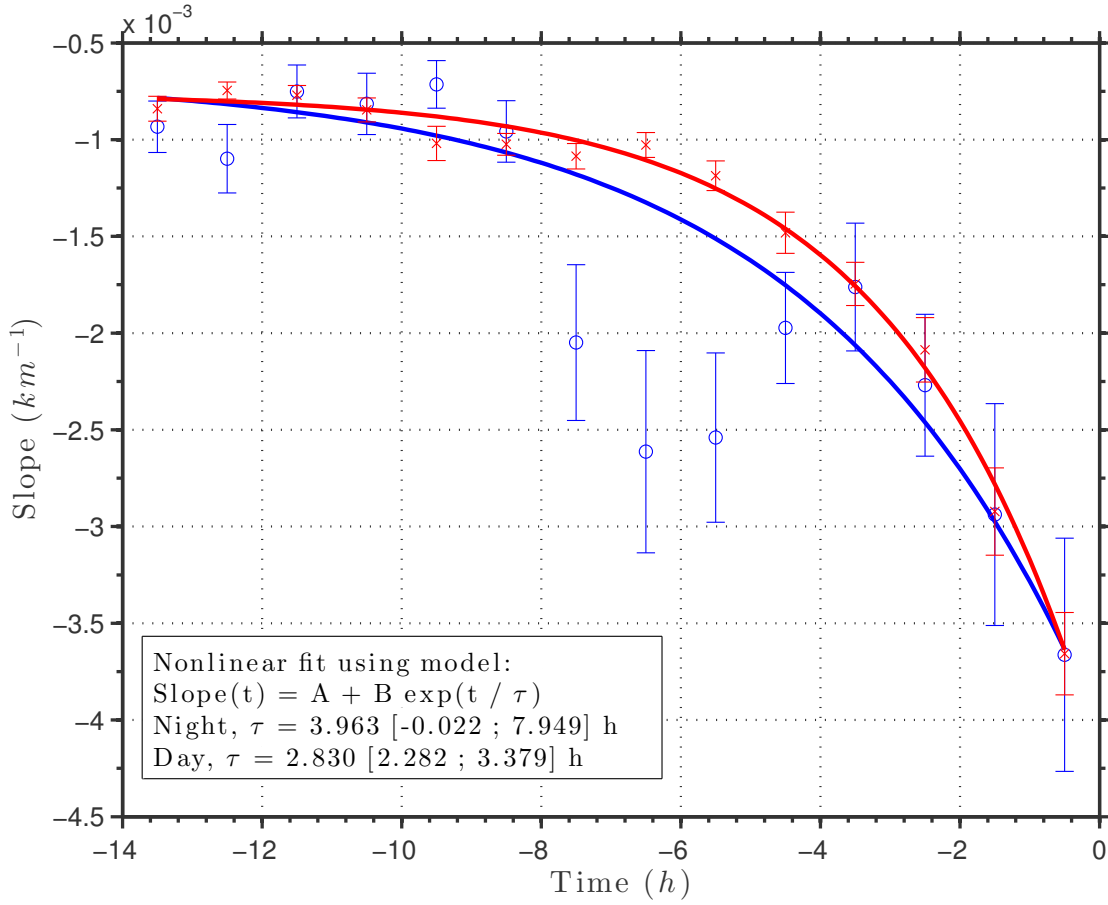


FIG. 6. Temporal evolution of correlation vs separation distance slope with exponential fit and error bars for diurnal (55 events, red) versus nighttime (12 events, blue).

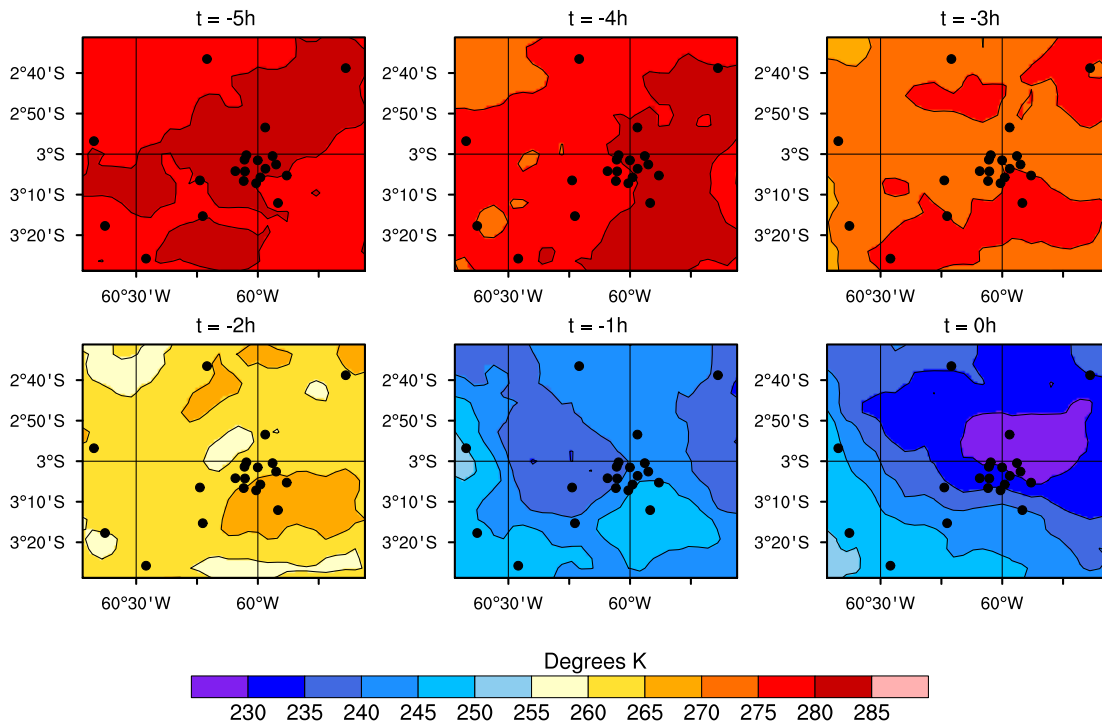


FIG. 7. Plot of the temporal evolution ($t = -5h$ to $t = 0h$) of GOES cloud top temperature (K) fields calculated
for 55 diurnal convective events.