Microclimate Analysis of Observations in a Master-Planned Residential Community in Arizona

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Introduction

➢The urbanization process affects microclimates, which are distinct small scale (~10^0 – 10^2 m^2) weather controlled by variations in urban structure, cover, fabric and metabolism (Oke 2006). Understanding how to best manage these microclimates through urban planning and design are important for stakeholders in residential areas (e.g. Mills et al. 2010).

➢The management of microclimates to enhance urban sustainability through reducing exposure to environmental hazards (e.g. heat island and thermal discomfort effects) is an important goal in applied geographical research, especially in the desert Southwest US (e.g. Chow et al. 2012). However, results from detailed observations and case studies are lacking in the research literature.

➢Here, we present initial results from year-long microclimate observations from a planned residential community (Power Ranch, Gilbert, AZ) sited in Metropolitan Phoenix. In particular, we look at the influence of surface vegetation and outdoor water use on seasonal variations of mean station temperature.

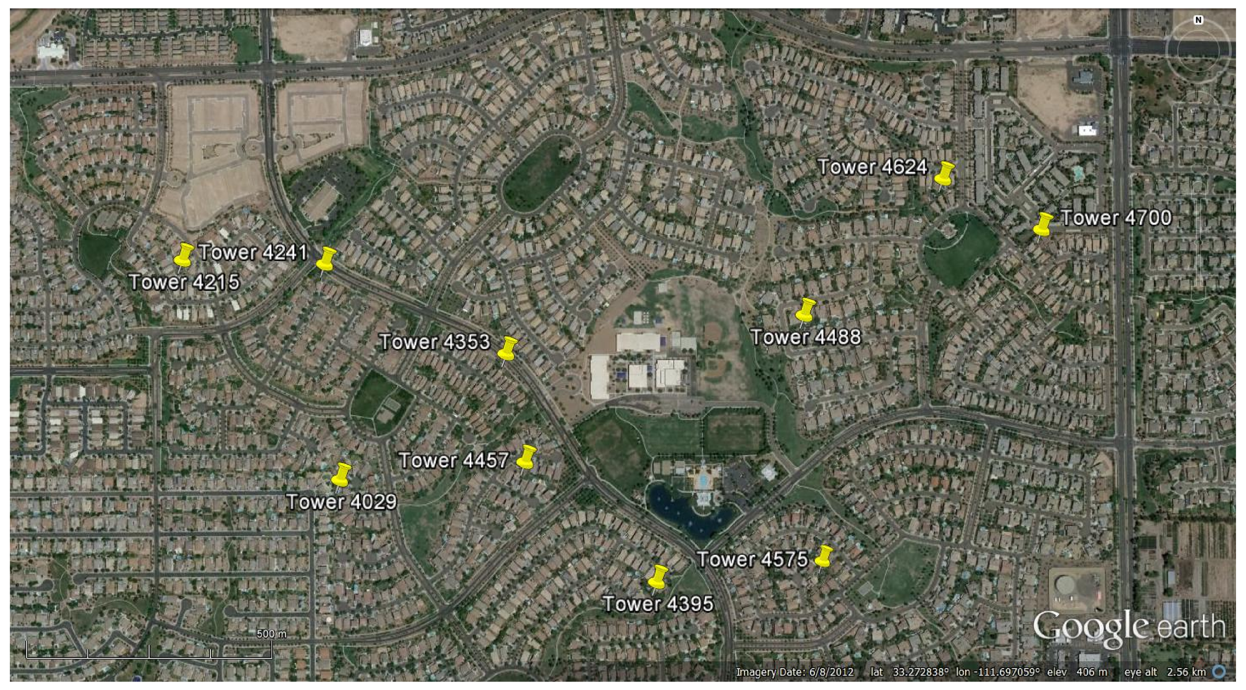

Fig. 1: Location of ten meteorological towers (marked as yellow pins) sited within the Power Ranch (PR) neighborhood (33.273° N, -111.695 °W) (Google Earth). The vertical dimension is ~1 mile.

Research Questions

➢How does vegetation and outdoor water use affect the urban microclimate of a residential neighborhood?

➢Do these impacts vary according to season (winter vs. summer) and spatial scale?

➢What are effective patch sizes, and can we separate patch-scale from neighborhood-scale and larger microclimate effects?

General Methodology

➢The master-planned residential community of Power Ranch (PR) is located in Gilbert, one of fastest growing suburban towns in the US. The US Census Bureau reported that its population nearly doubled from 109,000 in 1990, to 208,000 in 2010.

➢We conducted an intensive micro-climate monitoring campaign from Feb 2011–Jul 2012 involving a combination of microclimate stations and instrumental traverses throughout the study neighborhood (Fig 1; Table 1).

➢We obtained authorization from several homeowners to install weather stations in their back yards (WeatherHawk Signature Model 232; Fig. 2). In this study, we analyzed data from ten such weather stations from Aug 2011–Jul 2012, while summer and winter periods were defined as 14 day periods before and after each solstice (i.e. Jun 8 – Jul 6 and Dec 8 – Jan 5 respectively). These data were quality controlled prior to analysis.

➢Detailed GIS land cover data from the Town of Gilbert were also obtained. These data were used to derive study area land covers through an object-based image analysis (OBIA) method first utilized in Ruddell et al. (2010), and were also supplemented by periodic on-site ground-truthing surveys.

➢Residential outdoor water use at each station were documented at 15 min intervals with automated water meters and totaled for each hour. Permission from each homeowner was also obtained prior to installation of meters.

Table 1: PR weather stations and their descriptive land covers

PR Station	Yard Type	Site description
4029	xeric	shade trees, gravel mulch, swimming pool
4215	oasis	grass, gravel mulch, swimming pool, shade trees
4241	oasis	swimming pool, grass, gravel mulch
4353	xeric	gravel mulch
4395	oasis	swimming pool, grass, concrete walkway
4457	oasis	grass, shade trees
4488	oasis	swimming pool, grass, concrete walkway
4575	xeric	swimming pool, grass, concrete walkway, gravel mulch
4624	mesic	grass, shade trees
4700	oasis	grass, gravel mulch, shade trees

Fig. 2: WeatherHawk station sited at Station 4700. Each station measured hourly air temperatures, relative humidity, wind speed and direction, barometric pressure, and an evapotranspiration value derived from observed climate variables.

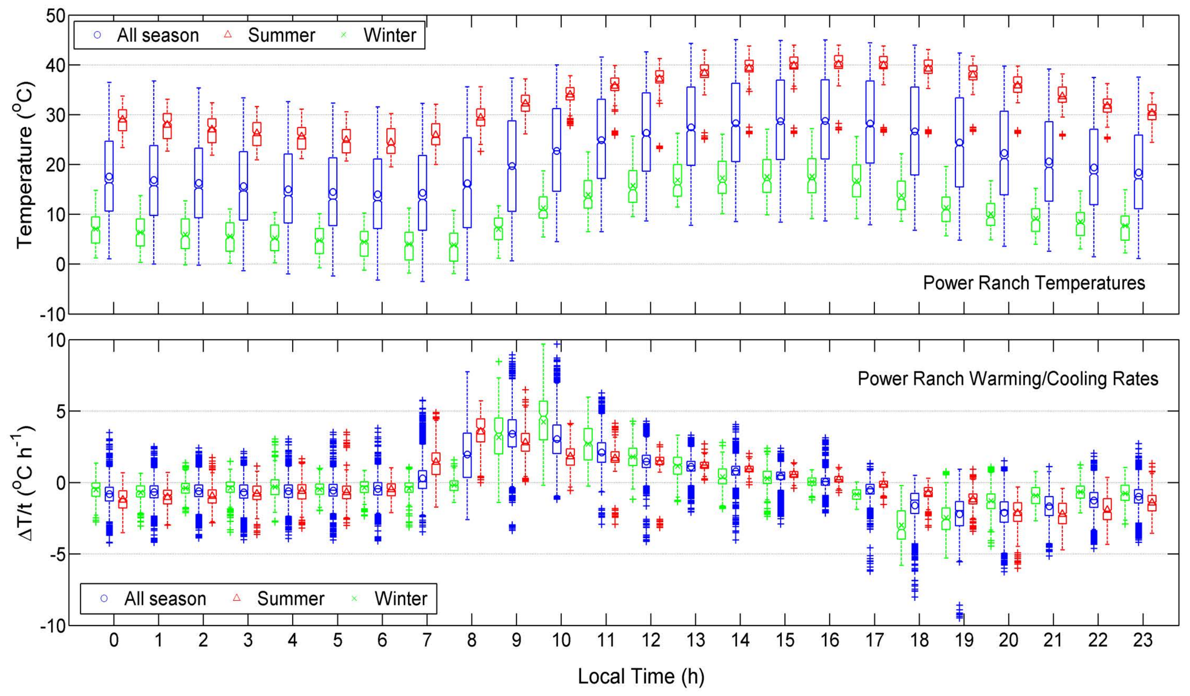

Fig. 3: Box plots of annual and seasonal mean hourly temperatures (T) (above) and hourly warming cooling rates (ΔT/t) (below) for all ten stations listed in Table 1

Results

➢Significant seasonal differences in mean station temperatures (T) at the local/neighborhood scale exist, but trends of seasonal hourly warming/cooling rates ($\Delta T/t$) are similar, with notable differences in timing of peak warming or cooling possibly due to variations of day length and/or soil moisture inputs (Fig. 3).

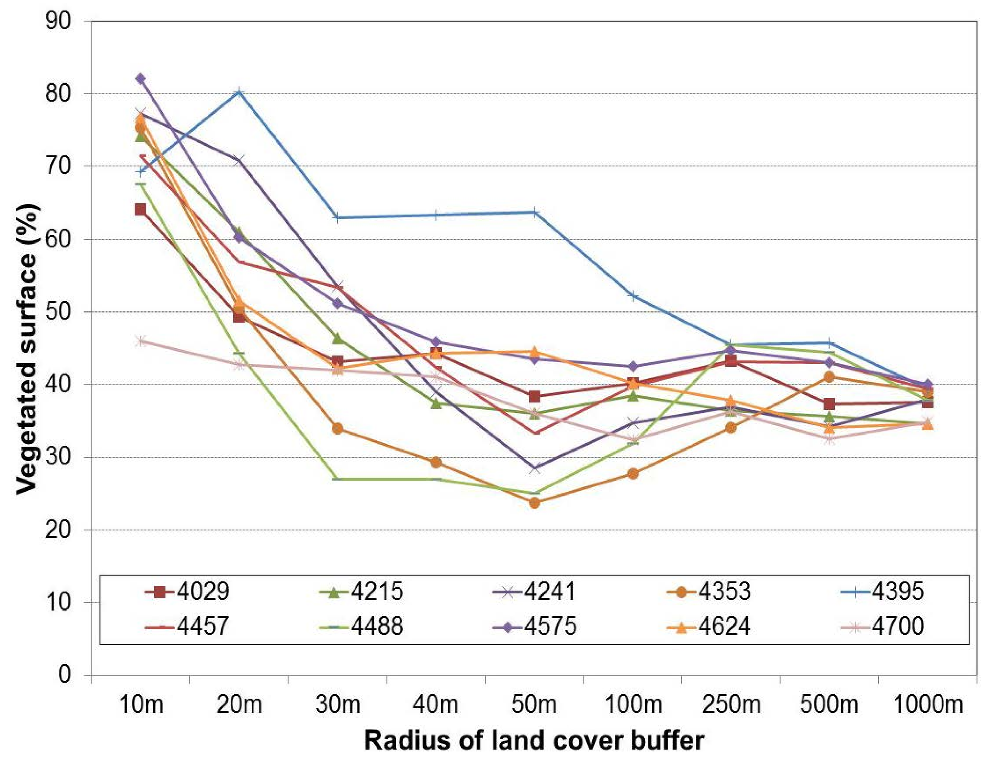

Fig. 4: Proportion of vegetated surfaces around a given radial distance from all PR stations based on OBIA analysis of land cover.

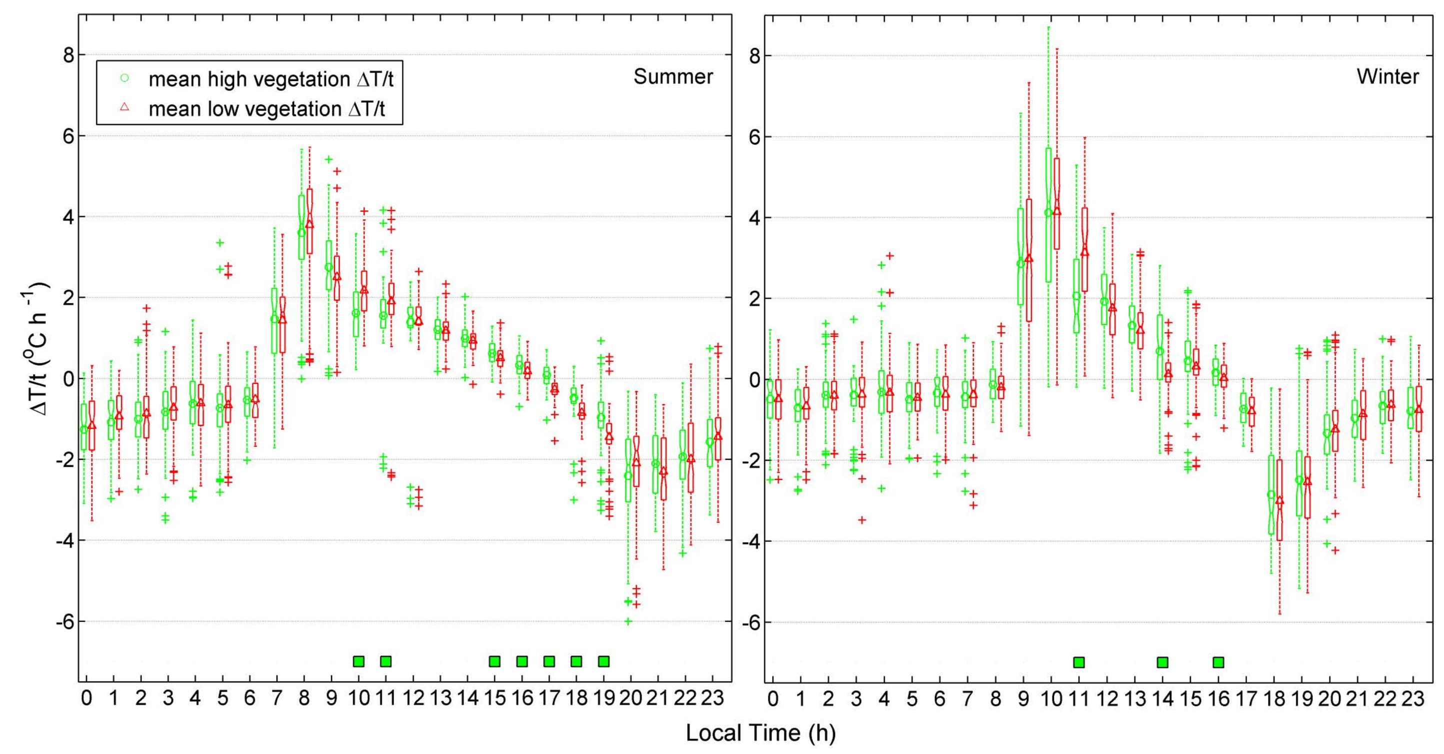

Fig. 5: Boxplots of mean seasonal ΔT/t for selected high and low vegetation stations. Significantly different ΔT/t at p<0.05 are marked by green boxes along x-axes

➢There exists significant variations of vegetation surface cover at the microscale (~<50), but cover converges to ~40% veg.

➢The three most (and least) vegetated microscale stations are grouped – 4241, 4395, 4575 and 4353, 4488, 4700 respectively. *ΔTgroup* is in Fig. 5. Significant differences exist in the afternoon.

Scaling Methodology

When air flows downwind from one patch to a different patch with different thermal and physical properties, this convective process affects microclimate downwind to a certain extent that is a fraction of the temperature difference between the patches. The patch scale radiative effect is difficult to directly estimate or observe, but is the essential signature of a patch's microclimate properties. Adapting and discretizing in time equations from Lee et al. (2012), for a patch 'A' amid a large heterogeneous matrix of surrounding patches, the time rate of increase of air temperature in the patch is ΔT^A, and is the net sum of the temperature-changing effects of convective 'C' and radiant 'R' processes affecting temperature, so,

$$\Delta T^A(t) = \Delta T^A{}_C(t) + \Delta T^A{}_R(t).$$

When wind speed is close to zero (approximated as U<0.3m/s, a low wind speed which is similar to the Weatherhawk's saturation speed), the convective term is dropped and only the patch-scale radiant term causes temperature change. Furthermore, adapting from Lee et al. (2012) eqn. 4, the convective term can be approximated as,

$$\Delta T^A{}_C(t) = (\ T^A(t\text{-}1) - \bar{T}(t\text{-}1)\ )\ \exp\left(-\frac{t_f}{L^A}\, k^A\, U^A(t\text{-}1)\right),$$

Where t_f is the elapsed time, 1 hour in this case, L^A is the patch size, approximated as 300m in this case (average minimum distance between towers), $\bar{T}$ is the average air temperature in the immediately upwind patches (approximated as the average of all patch temperatures excluding patch A), and k^A is a sensitivity factor which is larger when a patch is more sensitive to convective effects (due to canopy structure, shielding, topography, patch size, etc.). This implementation fails for arrays much smaller than U^A x t_f (because then $\bar{T}$ is not representative of the source area) or if there is a lot of directional asymmetry in the sensitivity of A to convection (because $\bar{T}$ is not representative, and because k^A will vary directionally).

To estimate k^A, choose t = 5pm because $U^A(t\text{-}1) >> 0$ (neglect radiant effects) and $\Delta T^A{}_R(t) \approx 0$, so $\Delta T^A(t) = \Delta T^A{}_C(t)$; now only k^A is unknown. A sample of days yields a gaussian distribution of estimates of k^A (Table 2). These are generally $0 < k^A < 1$. The absolute value of $T^A - \bar{T}$ is used to fit. Summer n=29, winter n=14.

The convective effects $\Delta T^A{}_C(t)$ are plotted in Fig. 6. The radiative effects are estimated as the difference between the observed rate of change and the convective, so $\Delta T^A(t) = \Delta T^A{}_C(t) + \Delta T^A{}_R(t)$.

$\tilde{T}^A$ is the absolute value of the ratio between convective and radiative effects. It is a dimensionless number describing the dominant process at a patch at a specific time and place. It is plotted in Fig. 7, for summer.

	summer (1700hLT)		winter (1600h LT)	
Tower	k_mean	k_sd	k_mean	k_sd
T4029	0.218854	0.206401	0.097281	0.570151
T4215	0.260332	0.235289	0.345345	0.443295
T4241	0.185228	0.127236	0.357592	0.740756
T4353	0.165787	0.248421	0.375424	1.026617
T4395	0.051588	0.12186	0.309938	0.472019
T4457	0.093543	0.078294	0.36832	0.56429
T4488	0.178226	0.194278	0.071313	0.613434
T4575	0.140385	0.266078	0.431662	0.562897
T4624	0.132395	0.162003	0.365795	0.813063
T4700	0.749052	0.201367	1.75	0.882176

Table 2: fitted sensitivity factors k^A for patches, summer and winter. Values tend to ~0.2-0.3, but are higher in the winter, and for specific sites, indicating variation in the sensitivity of patches to convection depending on season and patch structure.

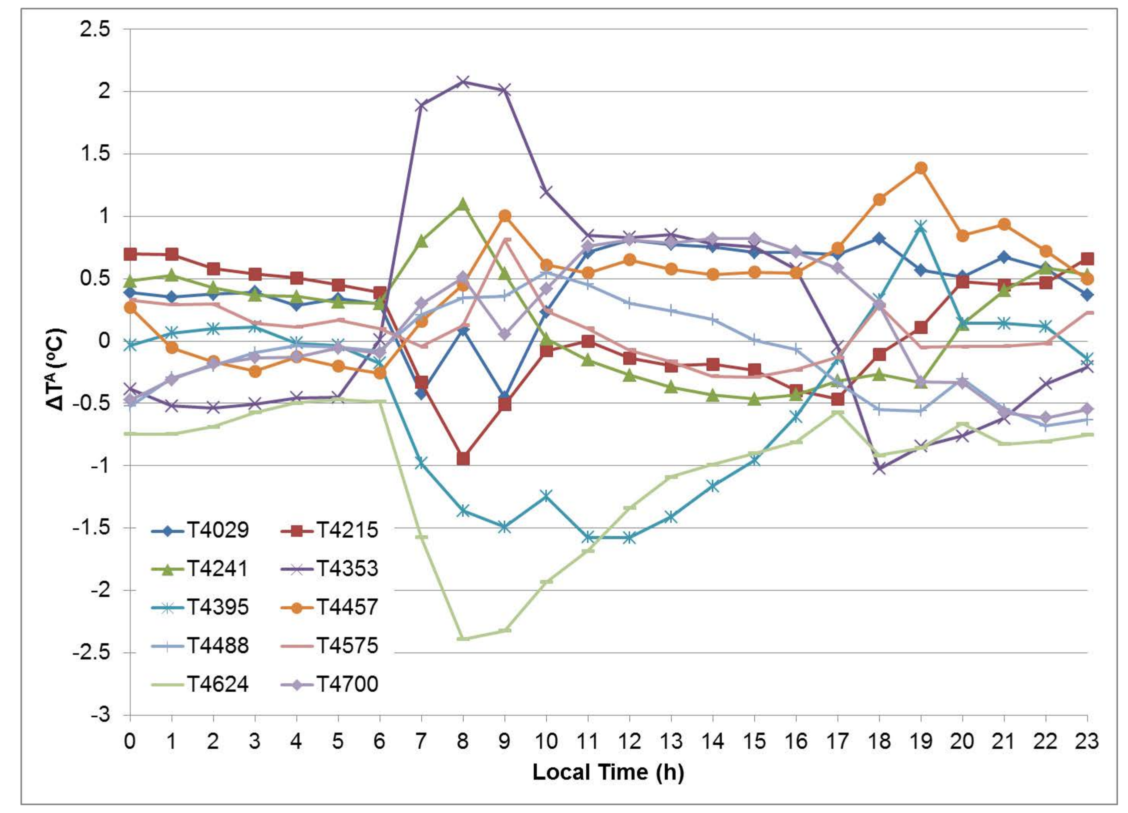

Fig. 6: Effect of convection on patch air temp., summer ensemble. Effects are strongest after sunrise and midday.

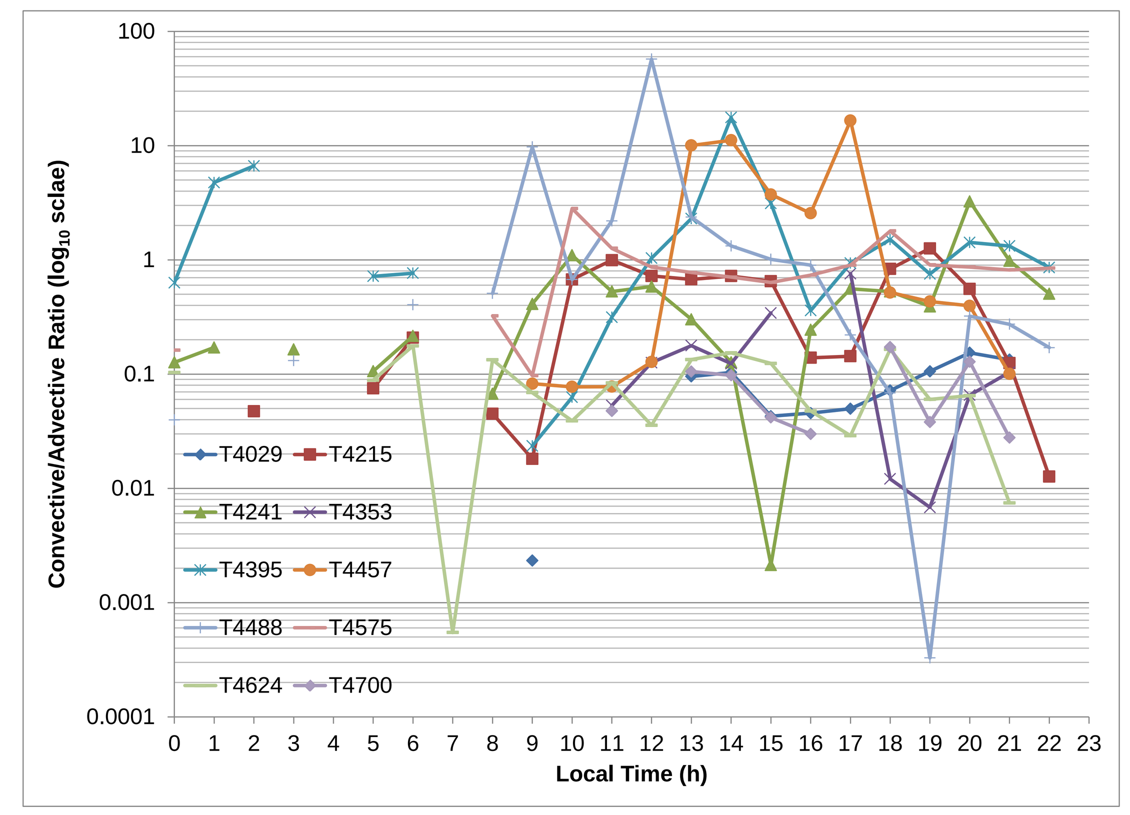

Fig. 7: Ratio of convective neighborhood scale effects to patch scale radiative effects on patch air temperature, summer ensemble. Significant differences in the controlling process exist between sites.

What explains the pattern? Comments please.

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