UNIFYING HOME ASSET & OPERATIONAL RATINGS: ADAPTIVE MANAGEMENT VIA OPEN DATA & PARTICIPATION

FESC Project Update October 13, 2014

1. PROJECT DESCRIPTION

PI: Mark Hostetler (Associate Professor, UF Department of Wildlife Ecology & Conservation)
Co-PI: Hal S. Knowles, III (Change Agent, UF Program for Resource Efficient Communities)
Supported Student(s): Hal S. Knowles, III (Ph.D. Candidate, UF School of Natural Resources & Environment)

External Collaborators: Nick Taylor (Ph.D. Student, UF School of Natural Resources & Environment), Jennison Kipp (Assistant In, UF Program for Resource Efficient Communities)

Description/Abstract: Recent environmental, social, and economic challenges are fostering a wave of interest in maximizing energy efficiency and conservation (EE+C) in existing U.S. homes. Long standing programs, ratings, and metrics are being reapplied into new stimulus initiatives such as the *Recovery through Retrofit*[1] program. Simultaneously, electric and gas utilities are expanding their demand side management (DSM) programs from weatherization and conventional technology replacement incentives to include conservation behavior campaigns with "recommendation algorithms" designed to assist in homeowner energy retrofit decision making. Furthermore, loan programs are emerging to address the financial barriers that commonly limit initiation of the necessary retrofits.

Collectively, these approaches most often project future home energy performance based on engineering models of the physical characteristics of homes (i.e., "asset ratings"). Yet to date, the marketplace is inadequately integrating historical household energy consumption patterns (i.e., "operational ratings") into the decision tree to optimize retrofit program efficacy and consumer benefits. Moving toward the unification of asset and operational ratings is crucial for successful program management, proper monitoring/measurement/verification (MMV), loan risk assessment, and for the persistence of reduced home energy use over time. However, unification will not be easy. This research project combines qualitative and quantitative research methods in social science and building science using Florida case studies to evaluate the opportunities and constraints of asset and operational rating unification and the steps necessary to get there. Relationships between our project and the collaborative, transparent, and participatory nature of "open government" initiatives are also being explored.

The secondary supplemental research will expand on themes and insights gained through the first phase of this existing FESC project. Specifically, these insights suggest that even when adding operational data to building asset data, the reductionist approach to evaluating home energy performance by controlling for known variables may continue to offer an incomplete picture of the complexities of performance trends and the influence of unknown and/or misunderstood variables. Furthermore, the home improvement industry may need to consider the possibility that the magnitude of total energy consumption, while a worthwhile metric and with its net reduction a worthwhile goal, is also an incomplete indicator of home energy performance optimization.

Budget: Original = $24,000 over two years ($12,000 from 01/01/2011 to 12/31/2011 and $12,000 from 01/01/2012 to 12/31/2012). Supplemental = $32,000 over 18 months (from 04/01/2013 to 09/30/2014) to cover a portion of the salary (at a rate of $22.20/hour) and fringe benefits (at a rate of 26.9%) for Co-PI, Hal S. Knowles, III. This equates to 36% (14.6 hours, or effectively 2 weekdays) of this Co-PIs weekly salary and fringe for the 18 month period.

Universities: University of Florida

External Collaborators: Nick Taylor (Ph.D. Student, UF School of Natural Resources & Environment), Jennison Kipp (Assistant In, UF Program for Resource Efficient Communities)

[1] See, http://www.whitehouse.gov/assets/documents/Recovery_Through_Retrofit_Final_Report.pdf

2. SUMMARY OF PROGRESS SINCE APRIL 2014

Phase one exploratory analysis of utility electricity consumption data at 15-minute intervals has begun for three years (FY2012, FY2013, FY2014) from a random sample of 450 residential customers within the JEA service territory. Evaluation of multiple methods was undertaken. Three probability distribution functions (HistPDF, MultiPDF, and RankCDF) suggested that these time series display power law scaling and may benefit from further nonlinear analysis (Figures 1-3). Rescaled range (R/S) analysis suggested that these time series display a complex pattern with a Hurst exponent ≥ 0.5 and ≤ 1.0 and may benefit form more in-depth fractal analysis (Figure 4).

Based on preliminary outputs from two variations of a detrended fluctuation analysis run within MATLAB, both residential electricity consumption time series and temperature time series appear to follow a multifractal pattern with the dynamics of variables changing at discrete time scales. At the 1-day to 16-day scales (MFDFA1), the multifractal patterns of the original time series are evidenced by multifractal spectra (Figures 5, 7, and 9) with widths and modes larger than those of pure white noise common to the randomly ordered time series (Figures 6, 8, and 10). At the 4-hour to 24-hour scales (MFDFA2), similar multifractal spectra characteristics in widths and modes appear in both the original (Figures 11 and 13) and the randomly ordered (Figures 12 and 14) time series.

While multiple analytical inputs have been tested (i.e., various minimum and maximum scale thresholds and various polynomial trend order "m" values), further exploratory analysis is necessary to find the optimal balance of time series smoothing without introducing problematic artifacts from overfitting. For example, in the temperature time series, a polynomial trend order of m=6 (Figures 7 and 8) provides a cleaner, smoother, and potentially more meaningful, multifractal spectrum than an m=2 (Figures 9 and 10). Literature in this field of analysis suggests polynomial trend orders of 1, 2, or 3 are most common. However, the minimum scale (i.e., the smallest number of time series readings) analyzed is often considerably smaller (e.g., 16 readings) than the minimum scale in our MFDFA1 analysis (e.g., 96 readings). We believe our larger minimum scale may allow for a higher order polynomial trend fitting.

These initial findings suggest that the actual trend of utility electricity smart meter readings over time provides valuable feedback about the performance of each home as a system beyond mere cumulative energy consumed. Once the optimal multifractal detrended fluctuation analysis inputs and methods are identified, we will generate a methodology manuscript describing the various approaches evaluated and summarizing the distribution of multifractal spectra as correlated to cumulative energy consumed. A second manuscript will evaluate correlations between residential electricity consumption patterns, building asset characteristics (e.g., size, year built, number of beds, number of baths) and key weather patterns.

HistPDF, MultiPDF, and RankCDF

Fractal Analysis in the Social Sciences
by Clifford T. Brown and Larry S. Liebovitch
http://www.ccs.fau.edu/~liebovitch/matlab.html

Figure 1. Example Signal (JEA FY2012/13) – HistPDF (Exponential Trend)

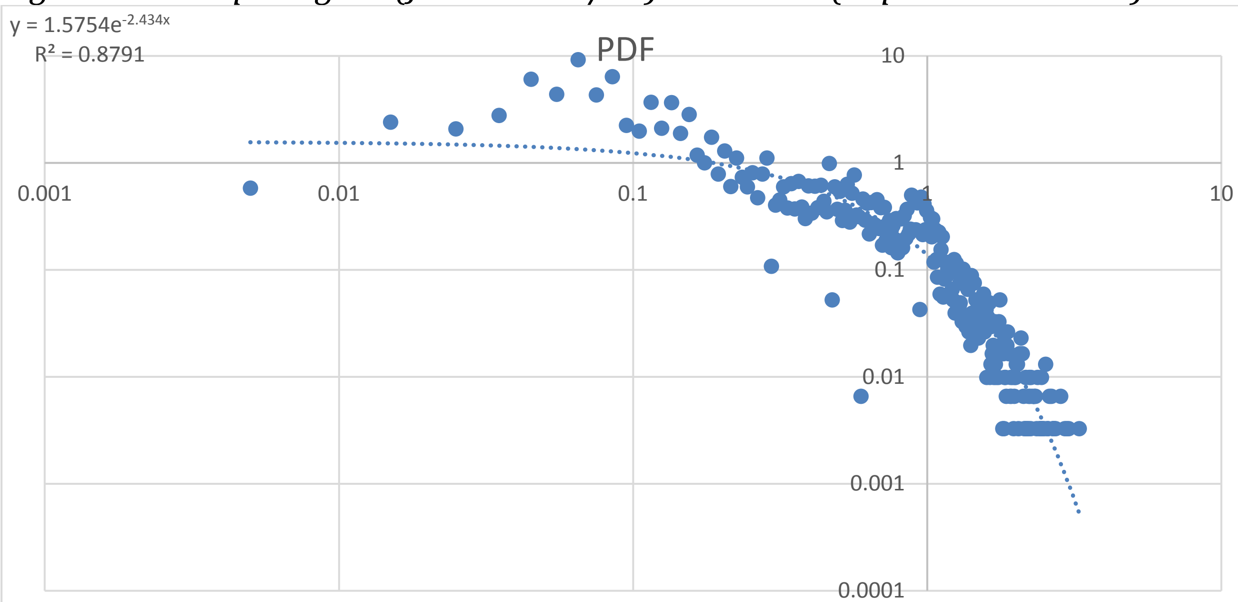


Figure 2. Example Signal (JEA FY2012/13) – MultiPDF (Exponential Trend)

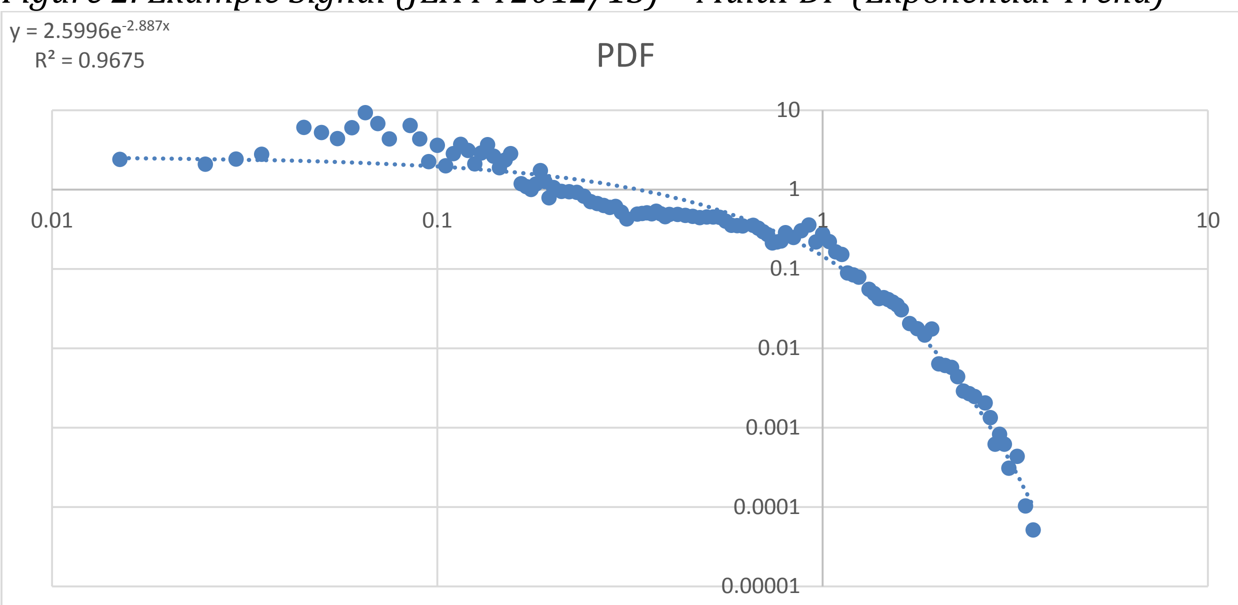
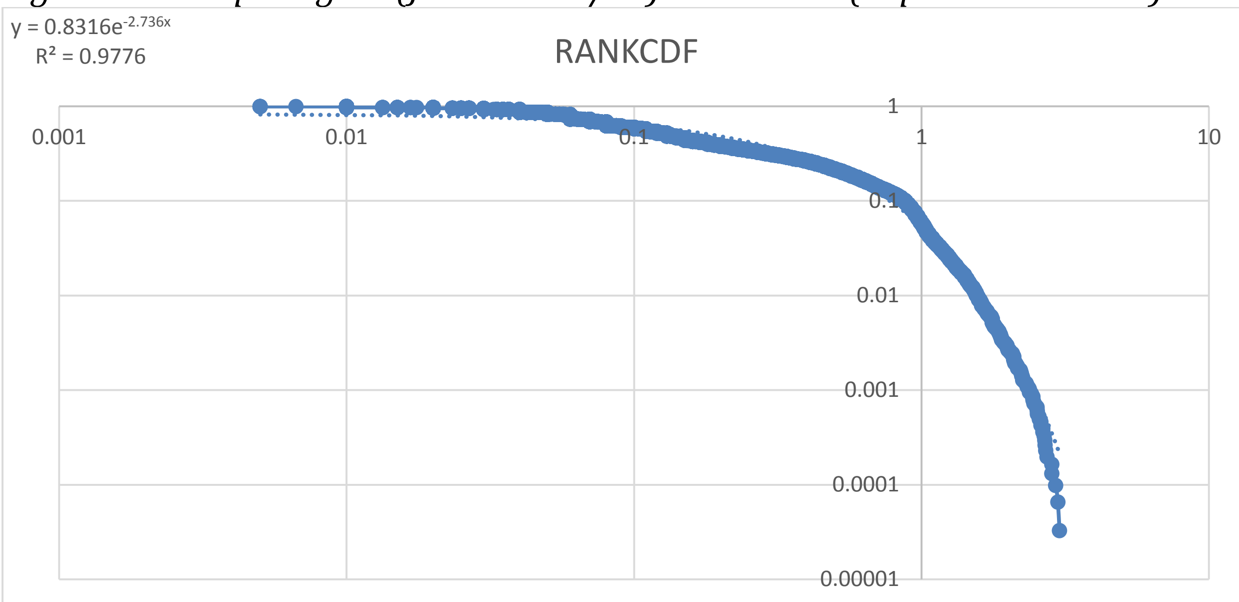


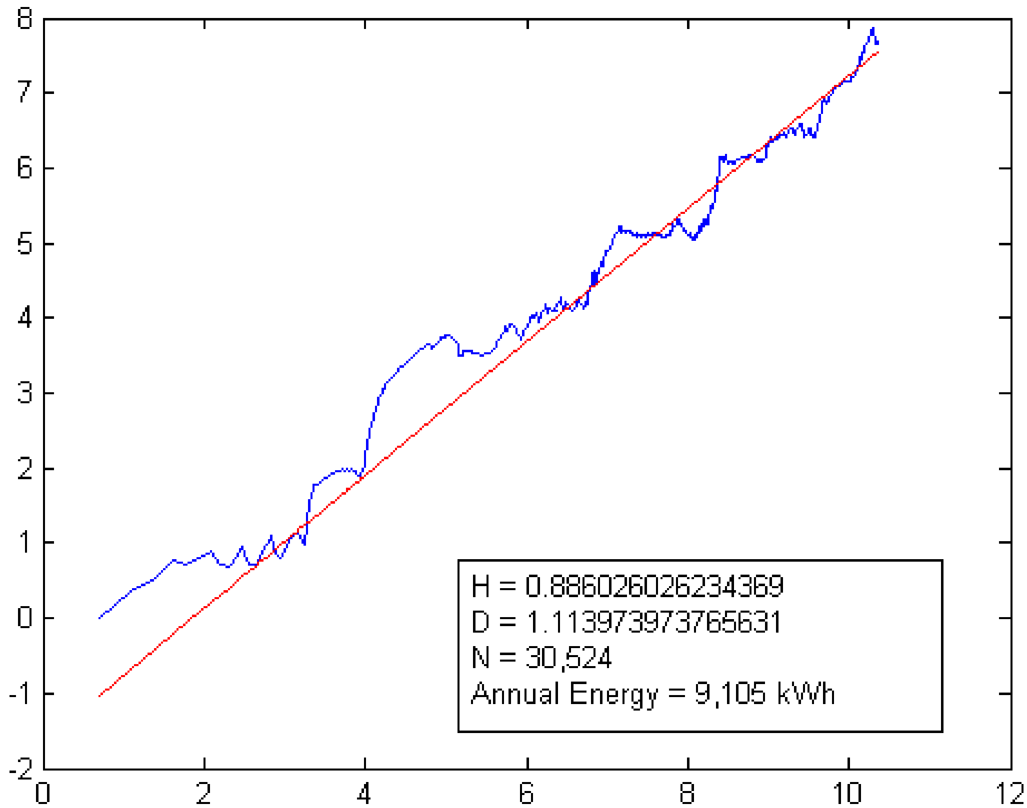
Figure 3. Example Signal (JEA FY2012/13) – RankCDF (Exponential Trend)



Rescaled Range (R/S) Analysis to Estimate Hurst Exponent

Hurst Exponent Estimation
by Vilen Abramov
http://www.mathworks.com/matlabcentral/fileexchange/39069-hurst-exponent-estimation

Figure 4. Example Signal (JEA FY2012/13) – Hurst Exponent (H) and Fractal Dimension (D)



Multifractal detrended fluctuation analysis

Introduction to multifractal detrended fluctuation analysis in Matlab
By Espne Ihlen
http://journal.frontiersin.org/Journal/10.3389/fphys.2012.00141/abstract
http://www.mathworks.com/matlabcentral/fileexchange/38262-multifractal-detrended-fluctuation-analyses

MFDFA1 (FOR SCALES FROM 1 DAY TO 16 DAYS)

Figure 5. Example Signal (JEA FY2012/13) – Original Time Series Order (m=2)

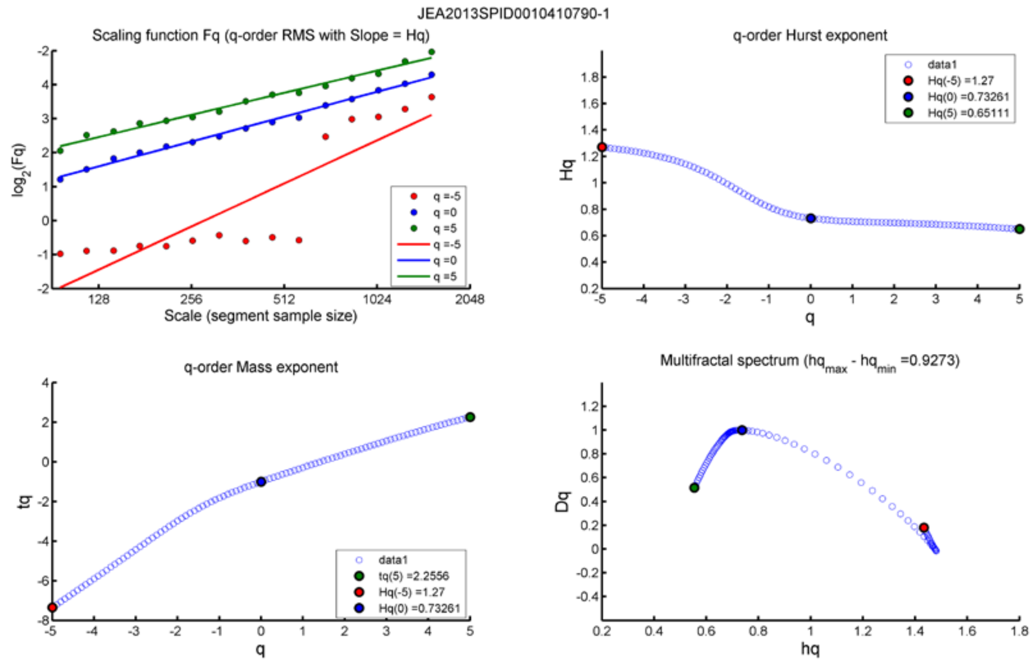


Figure 6. Example Signal (JEA FY2012/13) – Randomized Time Series Order (m=2)

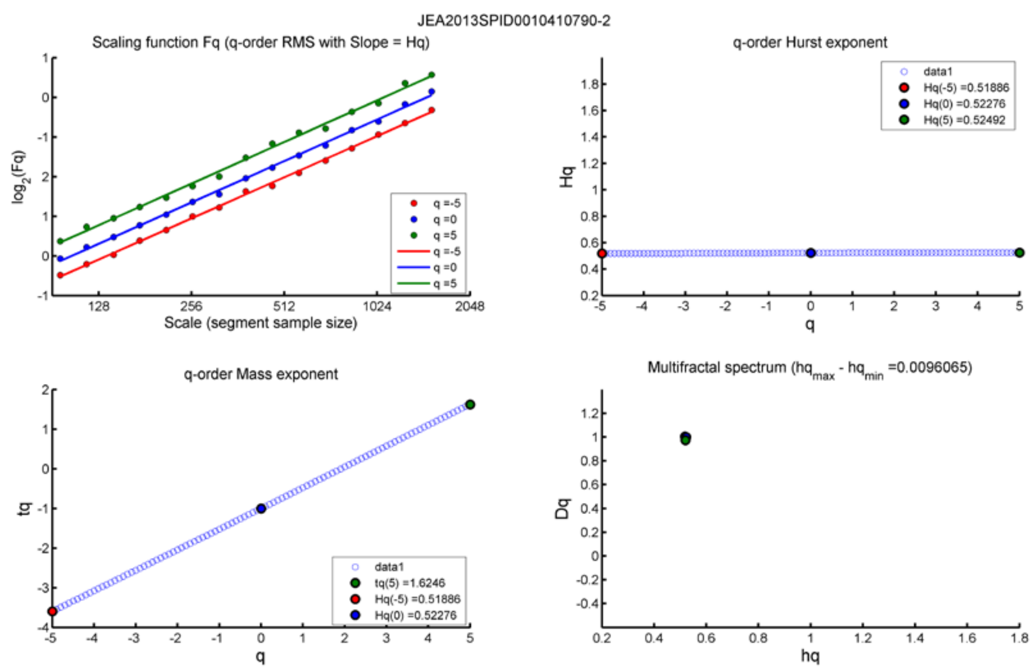


Figure 7. Temperature Signal (FAWN Station 180 CY2012) – Original Time Series Order (m=2)

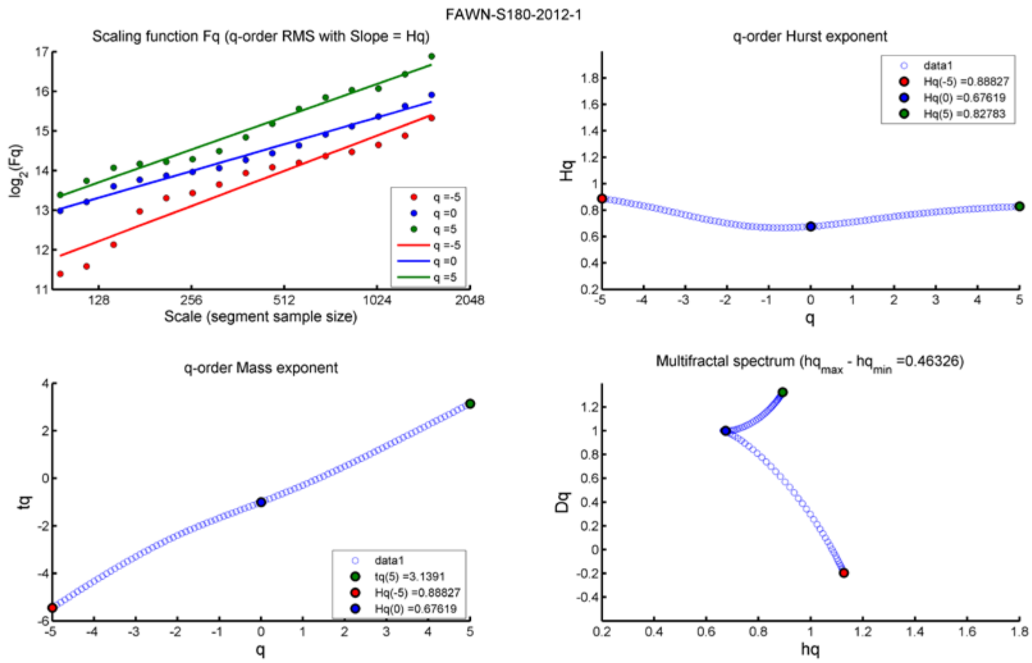


Figure 8. Temperature Signal (FAWN Station 180 CY2012) – Randomized Time Series Order (m=2)

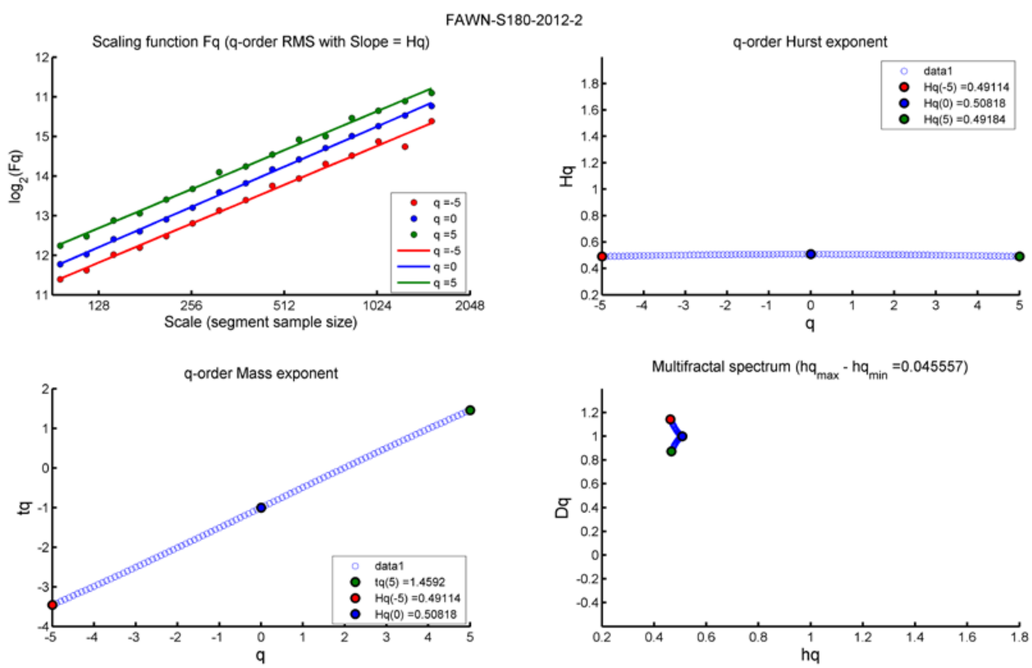


Figure 9. Temperature Signal (FAWN Station 180 CY2012) – Original Time Series Order (m=6)

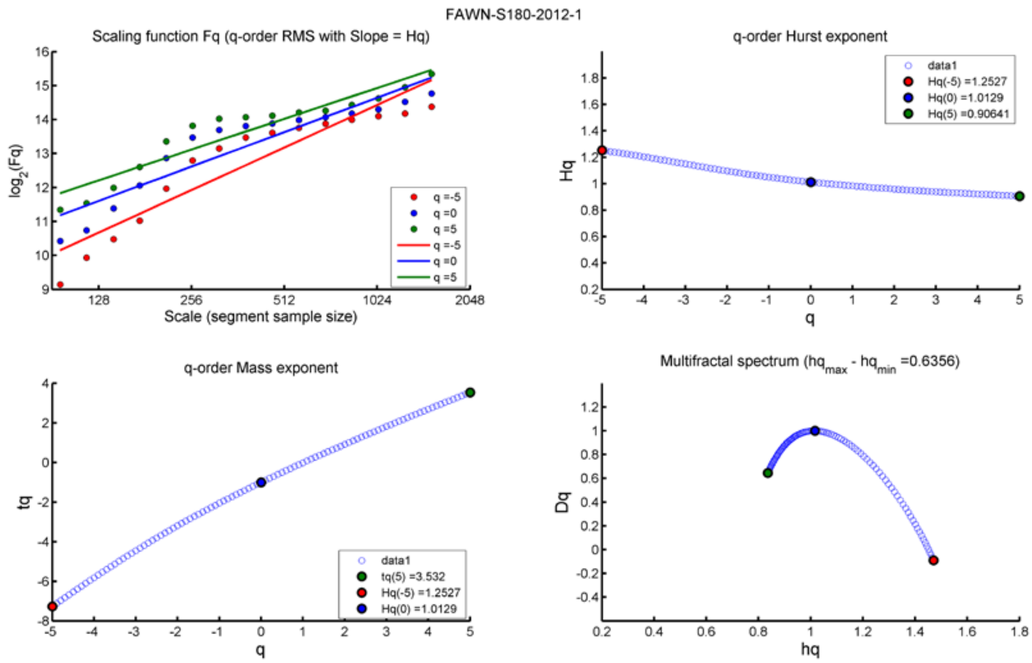
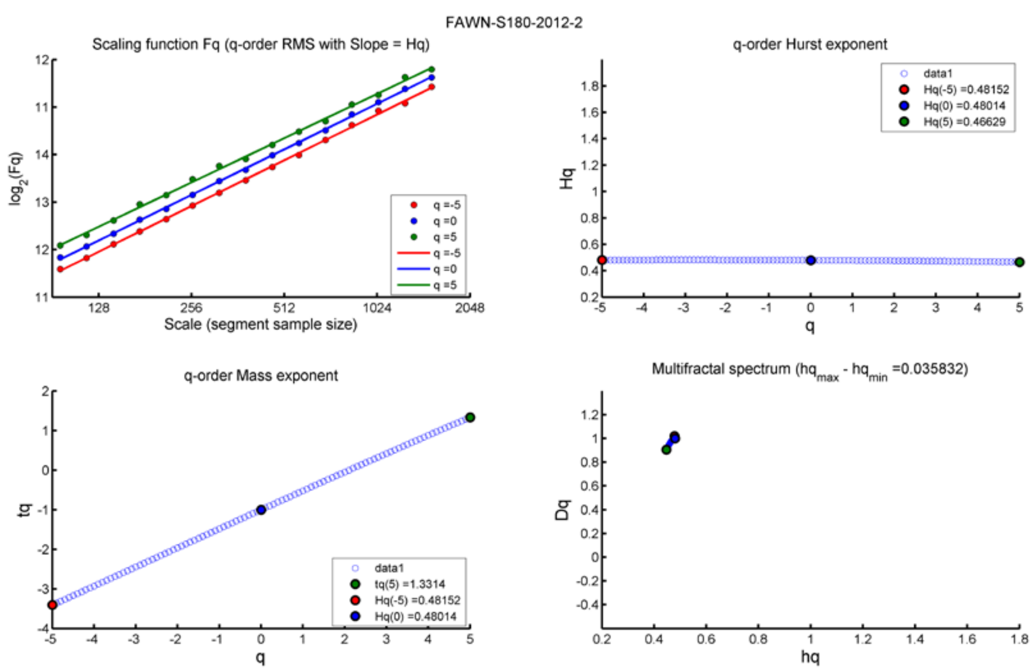


Figure 10. Temperature Signal (FAWN Station 180 CY2012) – Randomized Time Series Order (m=6)



MFDFA2 (FOR SCALES FROM 4 HOURS TO 24 HOURS)

Figure 11. Example Signal (JEA FY2012/13) – Original Time Series Order (m=2)

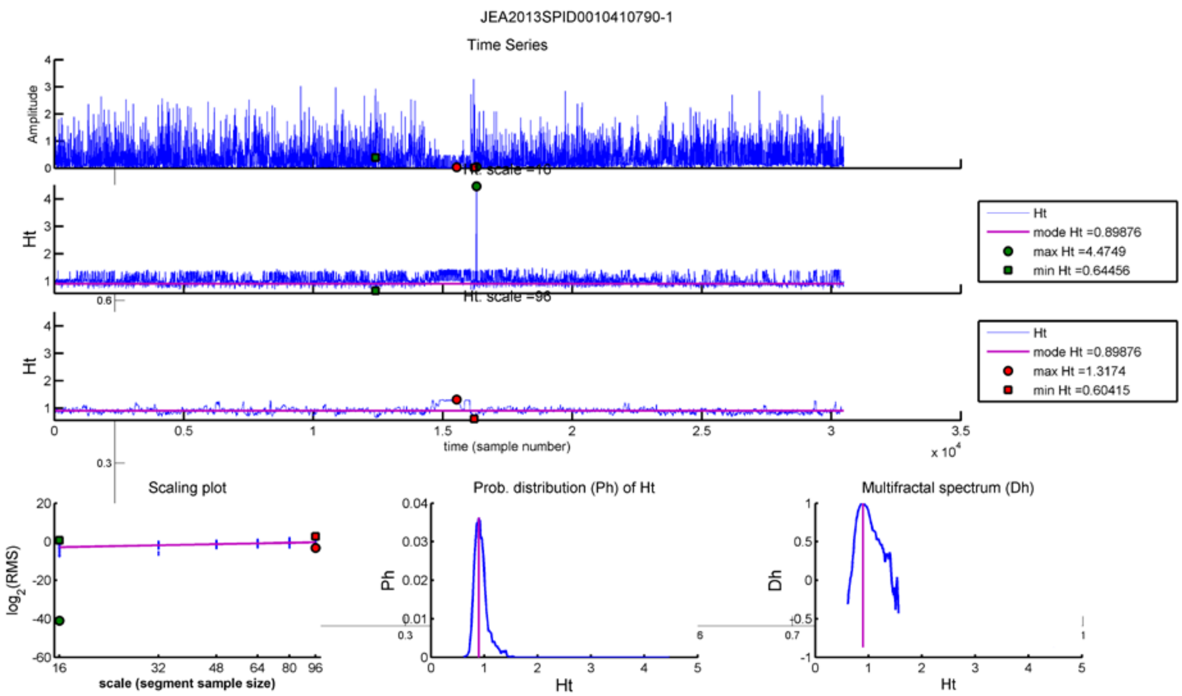


Figure 12. Example Signal (JEA FY2012/13) – Randomized Time Series Order (m=2)

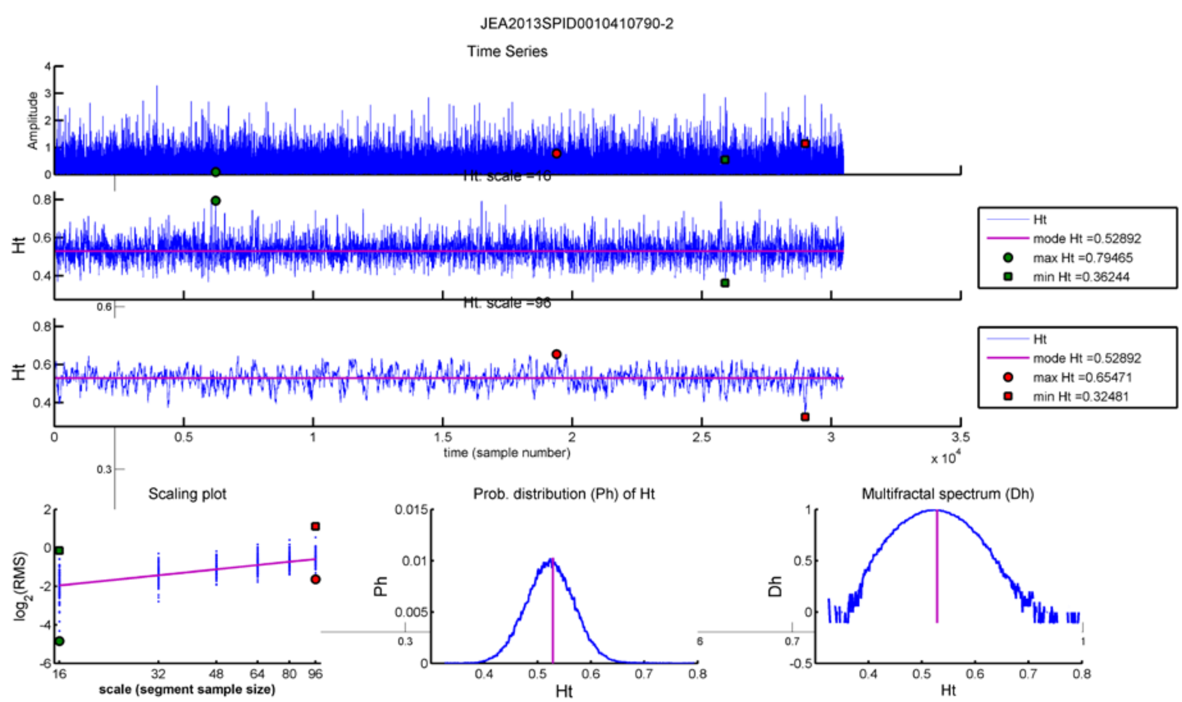


Figure 13. Weather Signal (FAWN Station 180 CY2012) – Original Time Series Order (m=2)

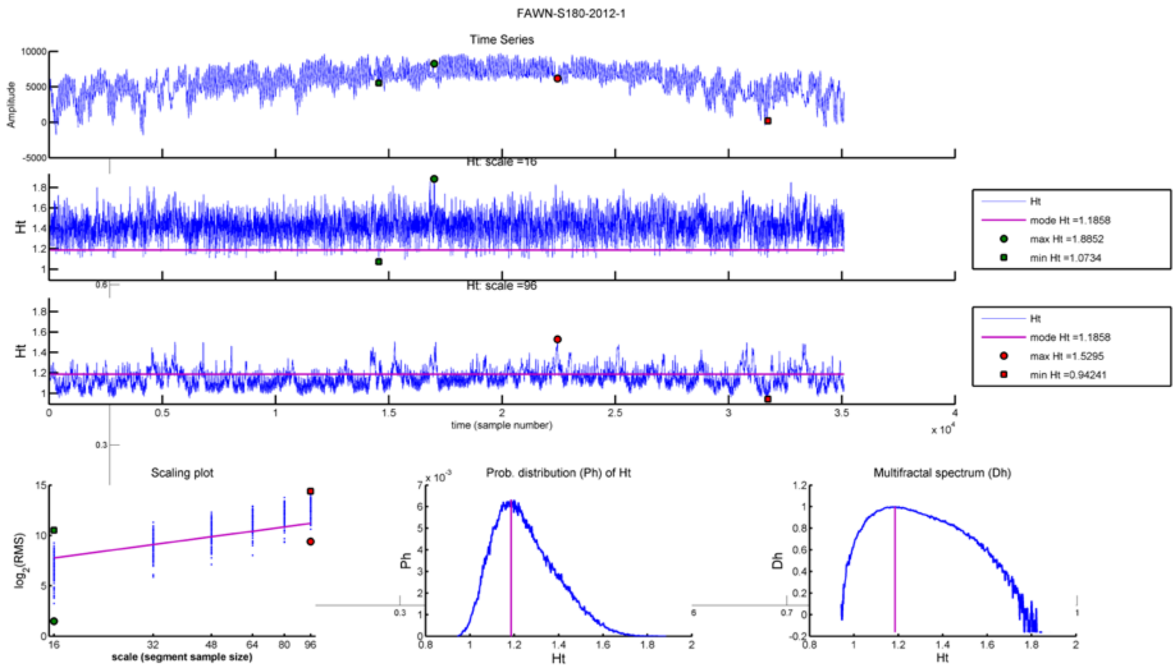
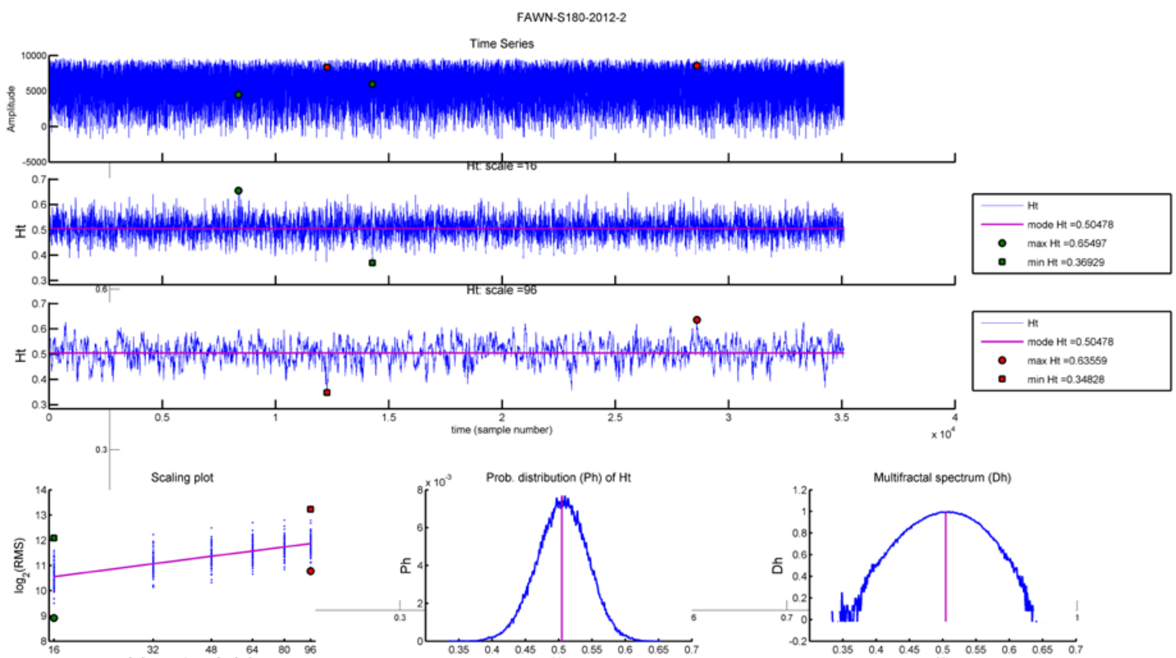


Figure 14. Weather Signal (FAWN Station 180 CY2012) – Randomized Time Series Order (m=2)



3. FUNDS LEVERAGED/NEW PARTNERSHIPS CREATED

New collaborations		
Partner name	**Title or short description of the collaboration**	**Funding, if applicable**
NOT APPLICABLE DURING THIS REPORTING PERIOD		

Proposal #1						
Title	**Agency**	**Reference Number**	**PI, Co-investigators and collaborators**	**Funding requested**	**Project time frame (1 year, 2 years, etc.)**	**Date submitted**
NOT APPLICABLE DURING THIS REPORTING PERIOD						

Grants / Contracts Awarded #1					
Title	**Agency**	**Reference Number**	**PI, Co-investigators and collaborators**	**Period of Performance**	**Funding awarded**
NOT APPLICABLE DURING THIS REPORTING PERIOD					