14C.8 STATISTICAL PREDICTION OF INTEGRATED KINETIC ENERGY IN NORTH ATLANTIC TROPICAL CYCLONES

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1. INTRODUCTION

Over the past few decades, predicting track and intensity fluctuations of North Atlantic tropical cyclones (TCs) has been a major emphasis for operational forecasters and atmospheric researchers alike. Both track and intensity metrics are definitively connected to the risks of a tropical cyclone, as maximum wind speed (V_{max}) is related to the maximum potential destructiveness of a storm's wind field (e.g. Emanuel 2005), and storm position is used to identify the regions at risk of experiencing the storm.

Despite the inherent usefulness of track and intensity metrics, they do not yield information on the size or overall strength of TCs. Over the past few Atlantic hurricane seasons, several notable landfalling TCs have produced more damage than otherwise would have been expected by a storm of its intensity. Hurricanes Ike (2008) and Irene (2011) both produced in excess of $15 billion in damage across the United States as noted by the National Hurricane Center's (NHC) tropical cyclone reports despite being rated as category two and category one storms respectfully at time of landfall on the Saffir Simpson Hurricane Wind Scale (SSHWS). More recently, Sandy (2012) only had a V_{max} of 70 knots when it made landfall as an extraordinarily large post-tropical storm, yet it caused in excess of $50 billion in total damage as per the NHC TC report. As a result of these recent damaging storms and those from the record-setting 2005 Atlantic Hurricane Season (i.e. Hurricane Katrina), some researchers have questioned whether or not intensity metrics such as maximum sustained winds, are best suited to communicate the risks of TCs (Kantha 2006).

Hurricanes Ike, Irene, and Sandy were all very large storms despite their weaker intensities. Therefore, it is distinctly possible that V_{max} is not significantly tied to damage potential in larger storms. Irish et al. (2008) found that storm size is significantly correlated to storm surge in Atlantic Hurricanes and recommended that while intensity scales adequately categorize wind damage, storm size must be considered to adequately categorize damage from flooding.

Consequently, new scales and metrics have emerged as a complement to the SSHWS that are more closely tied to the overall kinetic energy of tropical storms (Powell and Reinhold 2007; Maclay et al. 2008). Integrated kinetic energy (IKE) is one such metric that is calculated by accumulating one-half of the surface wind field squared (U^2) times the density (ρ) per unit volume over the entire volume domain of a tropical cyclone (Powell and Reinhold 2007), or more specifically,

$$(1) \quad IKE = \int_v \frac{1}{2}\rho U^2 dV \,.$$

Importantly, unlike maximum sustained wind metrics, IKE responds to changes in the overall size, strength, and intensity of a TC. Therefore, IKE and other similar kinetic energy metrics are hypothesized to correspond well to the destructive potential of TCs, particularly with regards to storm surge damage.

For example, Hurricanes Ike, Irene, and Sandy at their respective times of landfall in the United States had extremely high IKE values, despite their low intensities (Figure 1). Sandy, in particular reached a lifetime maximum of over 400 TJs of IKE just prior to landfall, giving it the second highest maximum IKE value in any Atlantic TC since 1990. Therefore, it is distinctly possible that forecasting IKE, as a complement to existing intensity metrics, could help to better assess the risks of landfalling Atlantic TCs, particularly for larger and less intense storms such as these examples.

Despite the potential usefulness of real-time IKE updates, there are limited resources currently available to forecasters that are specifically designed to assess the kinetic energy of a tropical cyclone. Therefore, we present a statistical model, named Statistical Prediction of Integrated Kinetic Energy (SPIKE), which can be used in real time for forecasting IKE fluctuations in North Atlantic TCs. Much like the operational Statistical Hurricane Intensity Prediction Scheme (SHIPS) used for forecasting V_{max} (DeMaria and Kaplan 1994;1999; DeMaria et al. 2005), SPIKE utilizes a multivariate linear regression model trained on a blend of environmental and internal storm-driven predictors, in addition to observed persistence metrics, to predict changes of IKE out to three days in the future.

2. DATA

2.1 Historical Integrated Kinetic Energy Record

In order to calibrate a statistical regression model for IKE, it is first necessary to obtain a historical record of IKE that can be used as the calibration model's dependent variable. In the absence of continuous wind field analyses, IKE can be estimated through a stepwise relationship with operational 34-knot, 50-knot, and 64-knot wind radii, the radius of maximum wind (RMW), and V_{max}, as detailed by Powell and Reinhold (2007). Therefore, the operational wind radii from the extended best track dataset (Demuth et al. 2006) are utilized to create a six-hourly record of IKE values for all North Atlantic TCs of tropical storm force intensity and greater over a twenty-two year training interval between 1990

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and 2011. The resulting IKE values in the historical dataset specifically measure the integrated kinetic energy only over the portion of the wind field where the wind speeds are of tropical storm force or greater (U > $18ms^{-1}$). This specific IKE quantity is selected because it is hypothesized to be closely related to storm surge damage potential by Powell and Reinhold (2007).

It should be noted that the historical wind radii dataset used to calculate historical IKE values is subject to year-to-year and storm-to-storm inconsistencies, as the accuracy of the historical wind radii is limited to the data available in the operational or post-storm analyses. Therefore, the historical IKE dataset could be subject to the same inconsistencies of data quality and quantity that is evident within the wind radii data in the extended best track data (Misra et al. 2013).

The relative frequency distribution of the six-hourly historical IKE data is shown in Figure 1. There are 5498 six-hourly IKE values included in our historical dataset from 1990 to 2011 (one IKE value for each six-hourly TC fix), and it is evident that Atlantic TCs most often have IKE values that do not exceed 25 TeraJoules (TJ). The mean IKE value in the dataset is 34.9 TJ, and the standard deviation is 43.0 TJ. In rare instances, TCs can briefly obtain IKE values greater than 300 TJ, typically near the end of their lifecycle.

2.2 Potential Model Predictors

In addition to the historical record of IKE, a pool of potential predictors must also be created to establish the relationships that will govern the statistical model. These predictors are carefully selected based on some of the understood relationships between a storm's environment and the factors that govern the size strength, intensity, and ultimately kinetic energy of a TC (e.g. Gray 1968; McBride 1995; Hill et al. 2009; Maclay 2008; Musgrave et al. 2012).

These environmental, storm-specific, and persistence predictors are gathered from a combination of the NHC best track data set (Jarvinen, 1984) and the SHIPS developmental data set (DeMaria and Kaplan 1999). The variables derived from the extended NHC best track data are storm-specific predictors, such as date, position, duration, intensity, and translational storm motion. The environmental variables, which encompass thermodynamic, dynamic, and moisture related fields known to affect TC behavior, are taken from the aforementioned SHIPS developmental dataset (DeMaria and Kaplan 1999). In all, thirty-one predictors were considered for this regression exercise.

It should be noted that the SHIPS developmental dataset, from which the environmental data is obtained, is not a forecast, and instead it utilizes analyses and reanalyses from the National Centers for Environmental Prediction (NCEP) to provide estimates for the observed environmental conditions experienced by each storm from genesis to dissipation. An operational real-time version of SPIKE will obviously require the predictors to be forecasted by numerical models, since the analyses and reanalyses are not available for future time steps in a real-time operational setting. Therefore, the SPIKE models discussed for the remainder of Sections 3-5, all of which utilize observations and SHIPS developmental data, are not meant to be forecasts or even hindcasts. Instead these regression models will provide an estimate for the maximum potential skill of SPIKE in the idealistic scenario that the forecasted predictors exactly match the future observations.

3. REGRESSION METHODOLOGY

The distribution of historical six-hourly IKE values is decidedly non-Gaussian as shown in Figure 1. In fact, the six-hourly total IKE values are approximately log-normally distributed, which is similar to the distribution of storm size as measured by the radii of vanishing winds (Dean et al. 2009). Therefore, it would be inappropriate to use linear regression to model total kinetic energy values. Instead, SPIKE will seek to predict changes in IKE for twelve evenly-spaced time intervals from six hours to seventy-two hours (6hrs,12hrs, … , 72hrs). Ultimately, these IKE changes are more normally distributed and thus, it becomes more appropriate to use multivariate linear regression. However, in order to create a model for each of these twelve forecast intervals, SPIKE regression models must be calibrated and validated separately for each forecast interval.

Based on the success of the statistical SHIPS model used to predict intensity change, we utilize similar regression methodology to construct our SPIKE model for IKE changes. As done by DeMaria and Kaplan (1994), both the dependent and independent variables are normalized prior to training the regression model. As DeMaria and Kaplan noted, normalizing the predictors allows for a comparison between coefficients for various predictors and forecast hours (1994).

To avoid over fitting in our SPIKE regression model, predictor screening must be utilized. Once again, we follow the lead of DeMaria and Kaplan's SHIPS model (1994, 1999), by using backwards screening. Backward predictor screening is done here by training the model upon all of the predictors for each forecast interval, and then repeatedly removing the single predictor with the least significant regression coefficient one at a time, until all of the remaining regression coefficients are significant at the p=0.01 level. Ultimately, this backward screening methodology retains a smaller subset of predictors that are used in the SPIKE model for each forecast interval. To make the SPIKE prediction model as uniform as possible across the forecast intervals, the same predictors are chosen for all intervals. These predictors are selected if their coefficients are significant at the 99% level for at least half of the forecast intervals. As a result, predictors may be used on intervals when their coefficients are not significant, but as pointed out by DeMaria and Kaplan (1994), when a predictor is not significant, its coefficient goes to zero and its influence on the regression model is diminished.

4. RESULTS

This section presents the results of the SPIKE regression model. In addition to estimating fluctuations of IKE, SPIKE will also be adapted to estimate total IKE by incorporating persistence values of kinetic energy. Finally, the predictive skill of SPIKE is evaluated in a standard bootstrapping exercise. An emphasis will be made in interpreting the physical relationships that drive the regression model in the first section, because a statistical relationship is meaningless without an understanding of the underlying physical processes.

4.1 Physical Interpretation of Selected Predictors

The predictors retained through the backward screening exercise are shown in Table 1. These predictors encompass a wide array of variables ranging from thermodynamical fields such as the depth of the 26°C isotherm to positional variables such as latitude, dynamical values like upper-level divergence, and persistence variables such as past values of IKE. For the sake of simplicity, the variables are referenced as they are abbreviated in Table 1 for the rest of this discussion.

The coefficients for these variables at selected forecast intervals are shown in Table 2. Encouragingly, the sign of most of the predictors' coefficients do not vary with forecast hour. For example, the coefficient for PIKE is negative in all intervals suggesting that storms with higher IKE are more likely to have decreasing IKE over time. As seen in the distribution of historical IKE values, TCs most often have low values of IKE; therefore it is not terribly surprising that higher IKE storms typically weaken. The physical reasoning behind this relationship is tied to the timing of maximum IKE during a TC lifecycle. As found by Musgrave et al. (2012), TCs often exhibit storm growth (increasing IKE) through most of their lifecycle. As a result TCs often have their highest levels of IKE late in their lifecycle, either prior to landfall or during extratropical transition (ET) when TCs often undergo wind field expansion as the RMW moves outward and the outer wind field accelerates (Evans and Hart 2008). Obviously following landfall or the completion of ET, TCs typically weaken drastically over the hostile environments of land or the cold northern Atlantic Ocean. Therefore, the negative coefficient of PIKE can be attributed to the negative IKE change of these strong storms, and the fact that weaker storms near genesis typically will gain IKE as they become more mature, providing the environment is not too unfavorable. Similar to PIKE, PDAY has negative coefficients for all forecast intervals. The negative coefficient is tied to the fact that TCs are more likely to have periods of increasing IKE close to the peak of the season (small PDAY), when conditions are typically most favorable for TC development.

The only predictor to have a coefficient that changes sign with forecast hour is dIKE12, wherein the coefficient is positive in the shorter forecast intervals and slightly negative in the longer intervals. The positive dIKE12 coefficients in the first several forecast intervals makes sense, as storms typically continue to have increasing IKE in most phases of their lifecycle (Musgrave et al. 2012), wherein a growing storm will continue to grow provided the environment remains somewhat favorable. Likewise, if a storm is in an environment unfavorable for IKE growth, the kinetic energy will likely continue to drop, at least in the short term. The slightly negative sign for the longer forecast intervals is more difficult to reason physically, but it should be noted that the coefficient is not significant to begin with, suggesting that past 12hr IKE change is only helpful for determining upcoming IKE changes in the immediate future.

In terms of the environmental predictors, some of the underlying physical relationships are immediately apparent. For example, the coefficients for VORT and D200 are positive, suggesting a direct relationship between storm growth and each field. In this case, both low-level vorticity and upper-level divergence are well known conditions that are generally favorable for large scale organized convection and the formation and development of TCs (e.g. McBride 1995). Similarly, the negative coefficients for MSLP and PENV are expected, as a more intense storm and/or a storm with a larger area of low pressure will typically have higher wind speeds and increased IKE with all else being equal. Likewise, the positive coefficients for RD26 are unsurprising, as TCs induce turbulent mixing and upwelling in the upper levels of the ocean which cools SSTs through the entrainment of cooler subsurface waters (e.g. Price 1981). This SST cooling mechanism plays a significant role of slowing down TC growth and intensification, especially for slower moving storms over shallow oceanic mixed layers (Schade and Emanuel 1999). Thus, an environment with a deeper thermocline, and a higher RD26, is more resistant to the negative SST feedback mechanism, making storm growth more favorable.

On the other hand, some of the physical relationships that drive the regression coefficients are less apparent. For example, the positive coefficients for SHRD and LAT seem somewhat counterintuitive to conventional TC development theories, wherein TCs favor low shear environments as well as warmer oceans which are typically found in the lower latitudes. However, as discovered by Maclay et al. (2008), TC growth can also be tied to external forcing from trough interactions and baroclinic environments over the higher latitudes. The positive coefficients for REFC for example reflect the positive influence of trough interactions on storm growth (Maclay et al. 2008; DeMaria et al. 1993). The positive coefficients of LAT and SHRD can also be related to ET. Extratropical transition occurs in the more sheared higher latitudes of the basin, and thus a wind field expansion from ET and the subsequent increase in IKE over the higher latitudes is likely influencing the signs of these coefficients. The coefficients for DTL also may seem counterintuitive as a storm over or near land will obviously weaken. However, TCs have lower IKE near genesis and become more mature later in their lifecycle, typically as they approach landmasses. Finally, the negative coefficients for RHLO are particularly counterintuitive because in most cases increased low level humidity is favorable for TC development and also for increased storm size (e.g. Hill and Lackmann 2009). However, this apparent contradiction can be explained going back to the relationship between increasing IKE and extratropical transition, whereas storms undergoing ET often have an intrusion of dry air into the storm circulation (Jones et al. 2003), thus decreasing RHLO. Therefore, it is possible that lower RHLO could be associated with expanding wind fields in ET or other similar events, but additional study of this physical relationship is clearly warranted.

4.2 Model Skill and Validation Tests

The shared variance between the SPIKE model and IKE variability is shown for selected forecast intervals in Table 2. As is the case with SHIPS (DeMaria and Kaplan 1994), the explained variance increases with increasing forecast hour. At first, this appears counterintuitive as forecast skill typically decreases with lead time. However, the average magnitude of IKE change from 1990 to 2011 is much smaller in the shorter forecast intervals than in the larger forecast intervals (9 TJ for 12hr; 32 TJ for 72hr). Considering the errors and biases within the historical archive of operational wind radii, the calculations for observed IKE likely have errors greater than the majority of IKE changes for the shorter forecast intervals. Therefore, the model will perform poorly at explaining these smaller, short term changes that are dominated by observational biases. Furthermore, the predictors used in SPIKE are observed and not forecasted. Therefore, this exercise is not hurt by forecast biases and errors. Instead this exercise is a proof of concept for forecasting IKE changes given idealistic perfectly forecasted predictors.

The shared variance scores of SPIKE for predicting kinetic energy changes are all significant considering the large sample sizes from using thousands of storm fixes between 1990 and 2011. The shared variance statistics for SPIKE are particularly impressive at the longer forecast intervals (r^2 = 0.54), where they approach and in some cases exceed the shared variance levels for SHIPS and TC intensity (DeMaria and Kaplan 1994; 1999). Admittedly, the model performs quite poorly in the shorter ranges, especially considering observed predictors are used instead of forecasted predictors.

Although SPIKE is designed to predict the normally distributed quantity of kinetic energy change, it can still be adapted to predict total kinetic energy (Figure 2). This is done by adding the estimate of IKE change from SPIKE to the known persistence IKE value. The shared variance levels between SPIKE's total kinetic energy estimates are significantly higher than its estimates for kinetic energy fluctuations. At a forecast interval of 12hrs, SPIKE can estimate total IKE with a staggering explained variance of 84%. This shared variance drops off to 70% by 30 hours and a still impressive 60% by a forecast interval of 72 hours (Figure 3).

The reason for this apparent increase of skill from predicting total IKE is a result of more predominantly incorporating persistence into the forecast. Since IKE is an integrated quantity, it is much more inertial than a quantity such as intensity. Whereas a point metric like maximum sustained wind can and does change rapidly somewhat regularly (e.g. Kaplan and DeMaria 2003), kinetic energy integrated across the entire wind field does not change as rapidly. Although drastic intensity changes do impact IKE values, rapid intensification (RI) events typically result in a drastic increase of near surface winds over a small confined area of convection near the center of the storm. Therefore, the impact on IKE during RI is typically small, provided the overall size of the storm's wind field remains somewhat constant. Therefore, a persistence forecast of total IKE is typically very skillful, especially in a short forecast interval. However, at longer forecast intervals, persistence does not fare nearly as well (r^2 = 25% at 72hrs; Figure 3). In fact, the SPIKE regression model is more skillful at estimating total IKE values at a 72 hour forecast interval than persistence is in forecasting the same quantity at a much shorter 30 hour interval. The lack of skill over time indicates that environmental and storm-specific data must be utilized for longer-term forecasts of IKE.

In addition to simply calculating shared variances over the calibration interval, some validation exercises are performed using standard bootstrapping techniques. These bootstrapping exercises are done by training the model over a sample that is created by randomly selecting data points from the overall population of IKE and predictor data (repetition allowed). The regression coefficients from the model trained over this sample are then used over the original population to examine how much skill is lost. In the case of the SPIKE model for kinetic energy change, there is an average decrease in shared variance of 3.7% across all twelve of the forecast intervals. The decrease of skill for the total kinetic energy estimates is less significant, averaging less than 0.5% across all of the forecast intervals. Ultimately, these simple tests indicate that SPIKE should be able to retain predictive skill when using a different sample of data. However, once again, because developmental SHIPS data is used for the predictors, there will likely be a decrease in skill when using forecasted predictors in an operational setting.

5. CONCLUSIONS

Although kinetic energy forecasts are uncommon in operations today, IKE is a metric that at the very least can complement forecasts of intensity metrics. Forecasts of IKE could potentially help forecasters to better assess the damage potential of a TC, particularly the risks resulting from storm surge in larger storms. Therefore, we designed a statistical regression model to estimate changes of IKE in Atlantic TCs out to 72 hours. The model created here explains as much as 50% of the variance in historical IKE changes out to three days.

More impressively, it is found that forecasting total IKE is more skillful when persistence is added to SPIKE's forecast for kinetic energy change. In fact, the model can explain more than 80% of the observed variance in historical IKE values at a 12hr forecast interval, trailing down to near 60% at 72hrs. The increase in skill is attributed to the inertial nature of the IKE metric. The fact that a persistence is a viable kinetic energy forecast in the short term could be used to the advantage of forecasters in assessing TC risks, especially considering the lack of recent improvements in forecasting the notoriously challenging intensity metrics (Rappaport et al. 2009).

Overall, this exercise serves as a proof of concept that when given accurately forecasted predictors, it is possible to forecast IKE in an operational setting. This work can be built upon by using IKE forecasts to statistically estimate storm size and wind field distribution. Future work will also be focused on adapting this model into a dynamical-statistical model that can be used in real time, while also continuing to build upon our understanding of the underlying physical processes that control kinetic energy variability.

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8. FIGURES AND TABLES

Variable	Definition	Units
PIKE	Persistence of IKE	TJ
dIKE12	Previous 12hr change of IKE	TJ
RHLO	850-700 hPa relative humidity	%
SHRD	850-200 hPa shear magnitude	kts
DTL	Distance to nearest landmass	km
D200	200 hPa divergence	10^{-7} s^{-1}
MSLP	Minimum sea level pressure	hPa
VORT	850 hPa vorticity	10^{-7} s^{-1}
LAT	Latitude of storm's center	°N
RD26	Ocean depth of 26°C isotherm	m
EPSS	Average difference between lifted surface parcel θ_e and 200-850 hPa environment θ_{es}	°C
PENV	Average surface pressure	hPa
REFC	Relative eddy momentum flux	$m \cdot s^{-1} \cdot day^{-1}$
PDAY	Number of days removed from peak of season (Sept. 10)	days

Table 1: Variables used in the SPIKE models. The coefficients for these variables are significant at the 99% level for at least half of the forecast intervals. Many of the variables (e.g. RHLO, SHRD) originated from SHIPS and are averaged over specific areas. For full details see the SHIPS predictor file (DeMaria and Kaplan 1999)

Variable	Forecast Hour				
	12hr	24hr	36hr	48hr	72hr
PIKE	-0.53	-0.70	-0.72	-0.70	-0.70
dIKE12	0.11	0.02	0.02	0.00	-0.01
RHLO	-0.13	-0.19	-0.22	-0.23	-0.25
SHRD	0.06	0.11	0.12	0.13	0.13
DTL	0.14	0.15	0.15	0.14	0.15
D200	0.12	0.13	0.12	0.12	0.11
MSLP	-0.26	-0.37	-0.39	-0.40	-0.41
VORT	0.16	0.19	0.20	0.20	0.20
LAT	0.24	0.30	0.33	0.34	0.36
RD26	0.11	0.11	0.10	0.10	0.09
EPSS	0.06	0.08	0.09	0.09	0.11
PENV	-0.08	-0.10	-0.13	-0.14	-0.18
REFC	0.07	0.08	0.07	0.05	0.04
PDAY	-0.08	-0.10	-0.11	-0.10	-0.08
Shared Variance	13%	25%	39%	43%	54%

Table 2: Regression coefficients for each predictor in the SPIKE model. The coefficients listed in a black font are significant at 99%. Shared variance between the SPIKE regression model, and observed kinetic energy changes are listed in the bottom row.

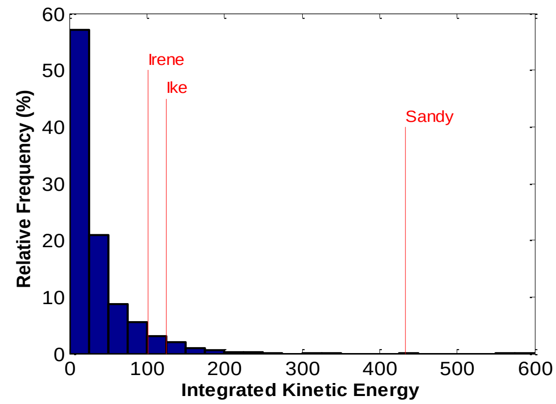

Figure 1: Relative frequency distribution of six-hourly IKE measurements in Atlantic TCs between 1990 and 2011. This sample includes 5498 fixes from 291 storms. Red vertical lines are shown to indicate IKE values for selected hurricanes just prior to a US landfall. The times of these IKE measurements are as follows: Irene 8/26/11 06Z; Ike 9/13/08 00Z; Sandy 10/29/12 18Z.

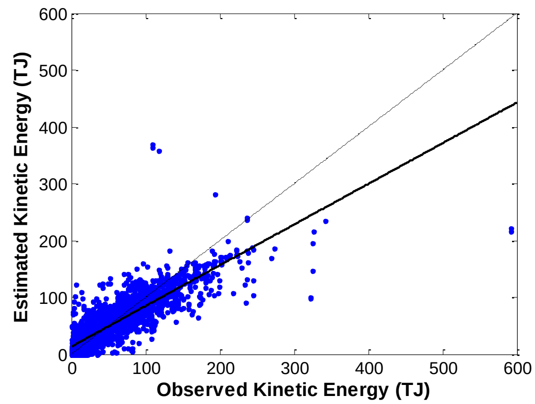

Figure 2: Scatter plot of observed total IKE values vs. estimated total IKE values from a 24-hour SPIKE regression model (blue dots). The dark black line represents the best fit line between the 4239 observed and estimated data points. The dashed line represents a perfect forecast (y=x).

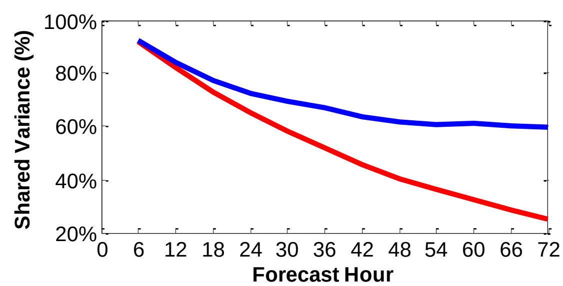

Figure 3: Plot of shared variance over forecast hour for total IKE. The blue line represents the shared variance between the observations and the SPIKE model. The red line represents the shared variance between persistence and the observed IKE value a certain number of hours later.