

PROJECT TITLE: Development of probabilistic drought intensification forecasts using the GOES-based Evaporative Stress Index

INVESTIGATORS:

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PROJECT YEARS: 3 year project (2014-2017)

TIME PERIOD ADDRESSED BY REPORT: September 1, 2014 – May 31, 2015

1. Project objectives and methodology

This project will develop a drought early warning toolkit based on satellite-derived maps of evapotranspiration (ET) and forecast output from the National Multi Model Ensemble (NMME) that will provide probabilistic drought intensification forecasts over weekly to monthly time scales. Recent examples of rapid drought development have demonstrated the need for a reliable drought early warning system capable of providing vulnerable stakeholders additional time to prepare for worsening drought conditions. The project will use the Evaporative Stress Index (ESI) dataset generated with the Atmosphere-Land Exchange Inverse (ALEXI) surface energy balance model and GOES satellite thermal infrared observations. The ESI represents standardized anomalies in the ratio of actual-to-reference ET and can be used to depict moisture stress in vegetation with high spatial resolution. Because the ALEXI model computes ET using remotely sensed land surface temperatures that respond quickly to changes in soil moisture content, the ESI is often able to detect increasing moisture stress sooner than other drought metrics, thereby making it a useful drought early warning tool. Temporal changes in the ESI have been shown to provide valuable information about the rate of drought intensification, thus other variables have been developed to encapsulate the cumulative magnitude of the ESI changes occurring over longer time periods. Prior work has shown a strong relationship between the magnitude of the ESI changes and subsequent drought intensification as depicted by the U.S. Drought Monitor (USDM).

Probabilistic drought intensification forecasts will be generated each week across the contiguous U.S. using the ESI and other relevant drought monitoring variables. New insight into the causes of rapid drought development will be gained through detailed analyses of soil moisture, rainfall, and atmospheric anomalies both preceding and accompanying recent flash drought events. Refinements will be made to the ESI-based drought intensification forecasts based on these insights and through development of synergistic methods that combine drought early warning signals from multiple data sources, such as the Standardized Precipitation Index (SPI) and soil moisture anomalies from the North American Land Data Assimilation System (NLDAS). After evaluating the efficacy of these drought intensification probabilistic forecasts, new methods will be devised to incorporate ensemble forecasts of temperature and rainfall from the NMME as a

means of further enhancing their forecast skill. The drought forecast products will be relevant to multiple end users, including authors of the NOAA Climate Prediction Center Seasonal and Monthly Drought Outlook products.

2. Research and accomplishments

During the past 9 months, we have developed an empirical method that can be used to estimate the current state of the USDM (e.g. by converting the discrete USDM categories into a continuous function) and forecast subsequent changes in the USDM over different forecast lead times. We have also assisted efforts to transition the research version of the ESI into NOAA operations and gathered datasets to perform a detailed analysis of the 2012 flash drought across the central U.S. to more closely analyze changes in vegetation health and soil moisture conditions during its evolution.

A) Transitioning the Evaporative Stress Index into NOAA operations

Prior work using the ESI to enhance our ability to monitor and predict drought conditions has used ESI datasets generated in a research setting; however, reliable access to these datasets is necessary to meet the long-term goal of this project of developing a reliable drought early warning toolkit. Thus, we are assisting an ongoing NOAA- and NASA-funded effort led by Co-PI Hain that is transitioning the ALEXI/ESI modeling system to NOAA operations. This system, which is known as the “GOES Evapotranspiration and Drought Product System (GET-D)”, is expected to become operational in August 2015 and will produce ESI datasets covering most of North America with 8-km horizontal resolution and the contiguous U.S. with 4-km resolution. We have assisted development efforts by evaluating prototype versions of the GET-D system and identifying errors in preliminary datasets. Once operational, these datasets (along with retrospective) analyses will be used during this project.

B) Developing empirical methods to predict drought intensification

An empirical method using logistic regression has been developed to predict the current and future states of the USDM using anomalies in the ESI, SPI, and NLDAS datasets. Because the USDM is a discrete variable, predicting its intensification over different time periods requires predicting a discrete yes/no variable for which logistic regression is well suited. Unlike standard linear regression, which minimizes the squared error between the predicted variable and the weighted sum of the predictors, logistic regression inserts the weighted sum of the predictors into the logistic function to predict the probability, p , that drought intensification will occur:

$$p = L(a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \dots), \quad (1)$$

where $L(x)$ is the logistic function $(1 + \exp(-x))^{-1}$ spanning from 0 to 1 as x goes from minus infinity to positive infinity, which ensures that the probability is always between 0 and 1. The parameters $(a_0, a_1, a_2, a_3, \dots)$ are fit using maximum likelihood.

When making predictions with multiple input variables it is essential to avoid over-fitting of the data, which can occur when there are too many predictors relative to the number of observations. With over-fitting, the model optimizes over the “random” variability in a given sample in addition to any real relationships that might be present. This may cause an over-fit model to perform poorly when applied to independent data. For this study, cross validation was used to

determine if a given variable adds real skill to the statistical model. This involves 1) removing one year of data from the analysis, 2) fitting the statistical model on all other years, 3) calculating the skill when applying the model to the year that was left out, and 4) repeating until all years have had a chance to be left out. We first performed cross validation to determine if an individual variable has skill. If the first variable has skill, we then repeat with the next variable to determine if two variables improve the skill. If adding the k^{th} variable degrades the model skill, then $k-1$ variables are used. To avoid artificially inflating the skill, all steps are calculated independently for each sub-period, including the calculation of anomalies and any standardization of the variables. The final result is the estimated skill and the number of useful predictors for each sub-period, which can then be used to determine the best predictors for all years.

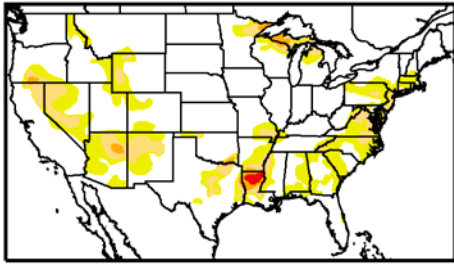
Next, we discuss an example of logistic regression used to predict USDM intensification over a 2-week time period given the 4 week precipitation totals, ESI, ensemble-mean top soil and total column (0-2 m) soil moisture from NLDAS (e.g., Noah, VIC, and Mosaic), and the changes in the ESI and NLDAS anomalies over one week. The chosen variables and compositing time periods are used here to illustrate issues we have encountered, and will be generalized later. The most important issue we have encountered when using many variables is the increased chance that the model will identify no useful predictors when there is actually useful skill. For example, using the predictors listed above, we find that 85% of grid points have useful skill east of 105°W ; however, if only a single predictor is used, such as precipitation, then 97% of the grid points have useful skill. Apparently, with a larger number of predictors the model is more likely to find random co-variability between unimportant predictors and the predicted variable that does not hold up when independent data is used. While on average the “real” predictor will have the strongest relationship and will therefore be chosen, with thousands of grid points there will be cases where a predictor will accidentally be included in the model only to be later rejected on the independent data. An additional issue when using many predictors is that adjacent points sometimes use different predictors and this can potentially lead to discontinuities in the predicted probabilities that are likely artificial in most cases. Due to these issues, it was necessary to explore ways to filter or combine the potential predictors beforehand so that fewer variables were provided to the cross validation step.

Because we know that the USDM authors use many drought indicators when constructing their weekly analyses, we take the approach of combining multiple variables into a single “master index” via weighted averaging. One approach to finding the weights would be to use the coefficients from multi-linear regression between the predictors and the predicted variable; however, because simple regression is prone to over-fitting, we chose to use a form of regularized linear regression to find the weights. Regularized regression methods introduce a penalty for complexity that typically favors models with smaller and/or fewer regression coefficients. Recently, Meinshausen (2013) and Slawski and Hein (2013) have shown that least squares regression with a sign constraint on the regression coefficients can be used without having to determine the “best” value of the regularization parameter. Because the sign of the relationship between the drought indicators and the USDM is known a priori (in the absence of random sampling noise), sign constrained regression is easy to apply in our case. To further reduce the potential for over-fitting, we apply the sign constrained regression to a $4 \times 4^{\circ}$ box surrounding each grid point when calculating the weights. Once the weights for the “master

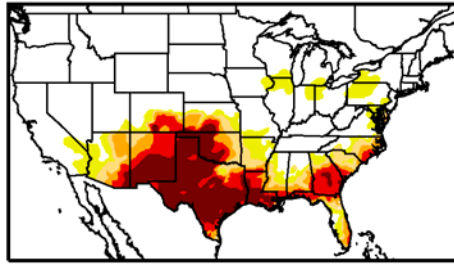
index” are computed, however, the fitting of the logistic regression and the skill scores are applied at each individual grid point. As with all other calculations, the weight calculations are cross-validated to ensure that the skill is not artificially enhanced. With this new method, the cross-validated variable selection procedure is fed a single index, which is a weighted sum of multiple predictors. This method greatly increases the number of grid points that have skill on independent data and allows multiple variables to impact the predictions. We also use this weighting procedure to determine the “optimal” compositing period when averaging each variable. For example, by feeding the sign constrained regression method the precipitation for the past week and at multiple time lags, the method computes the relative weights for each time lag. The advantage of our method is that any combination of *positive* weights will be included in the optimization, whereas simple regression would allow both positive and negative weights, but at the expense of over-fitting.

Because the USDM uses discrete categories, our results have shown that predictability can be gained by better characterizing its current state. For example, when the USDM is in the “no drought” category, it is useful to know whether conditions are near normal or unusually wet because this will have a large impact on future changes in the USDM depiction. Using this state information will also better leverage information from the ESI and NLDAS because the skill using the predictors discussed above is dominated by precipitation. In order to create an explicit statistical model with quantifiable predictions, we assume that there exists a hypothetical continuous, normally distributed version of the USDM that can be observed after it is artificially discretized based on the 70th, 80th, 90th, 95th, and 98th percentiles. We assume that in the absence of the discretization that simple linear regression would be a good model to relate the SPI, ESI and NLDAS to the USDM (i.e. the USDM state is linearly related to these predictors). Using these assumptions, the likelihood function is a function of the regression coefficients. For predictors, we use the SPI averaged over 4, 8, 12, 16, 20, 26, 39 and 52 weeks, the ESI averaged over the same time periods, and the NLDAS soil moisture averaged over 4 weeks for the 0-10 cm, 0-100 cm and 0-200 cm layers. Sign constrained regression is used to find the weighting of the predictors to create a master index. The model is fit using data from May through September from 2001-2014 and all results are cross-validated. Since the model predicts a continuous USDM index we use the best guess (in a least squares sense) discretized version of our prediction for comparison purposes. The observed and predicted USDM state for the middle of July for several years is shown in Fig. 1. The cross-validated correlation between the empirical model prediction and the USDM for the full record is shown in Fig. 2. Overall, the regression-based predictions of the current USDM state are very good with correlations exceeding 0.8 across much of the central and eastern U.S.

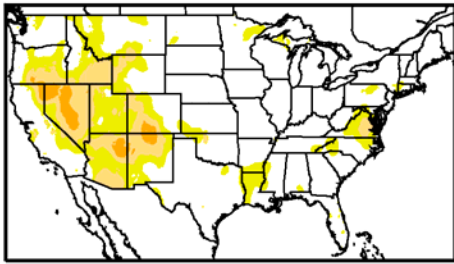
20JUL2010: USDM



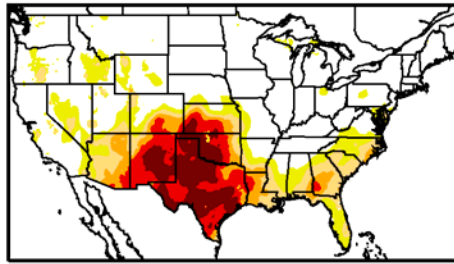
19JUL2011: USDM



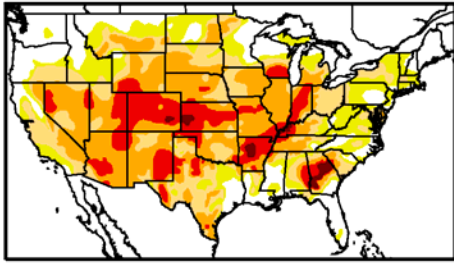
20JUL2010: prediction



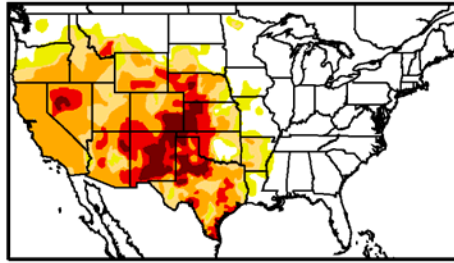
19JUL2011: prediction



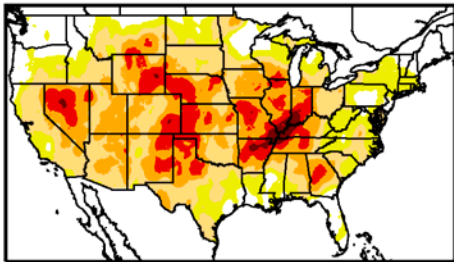
17JUL2012: USDM



16JUL2013: USDM



17JUL2012: prediction



16JUL2013: prediction

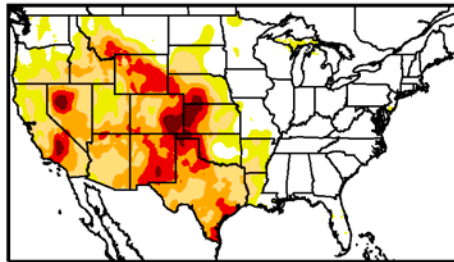


Figure 1: Observed and empirical-model estimated USDM drought analyses for 20 July 2010 (top left panels), 19 July 2011 (top right panels), 17 July 2012 (bottom left panels), and 16 July 2013 (bottom right panels).

temporal corr: USDM & prediction

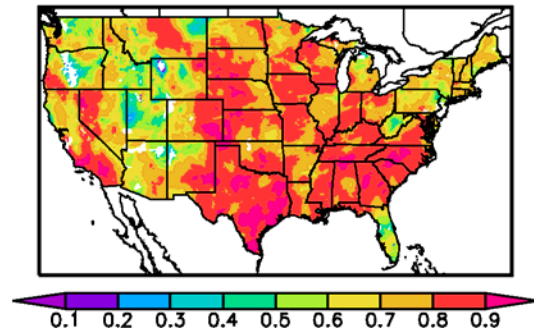


Figure 2: Correlation between the cross-validated observed and empirical model predicted USDM drought analyses using weekly data from May-September for 2001-2014.

There are different ways to use information from the USDM state model to predict the likelihood of an increase in drought severity. Our tests have shown that intensification in the USDM drought depiction is most strongly related to the ratio of two probabilities: 1) the probability that the USDM drought severity should be worse than the current analysis indicates (i.e. if the USDM depicts “no drought”, integrate the probability function from the 70th percentile upwards (call this P)), and 2) the probability that the USDM depiction should be less severe than currently indicated (e.g., $1 - P$). After looking at histograms of precipitation and the above “odds ratio” ($P/(1 - P)$) for times when the USDM intensifies versus times when the USDM does not, it was determined that the logarithm of the odds ratio is the best predictor.

Combining all this information showed that the best model for predicting increases in the USDM drought severity over 2, 4 and 8 week time periods involves precipitation at the 4 latest time lags (e.g. 4-16 weeks) and the “odds ratio” predictor from the USDM state model described above. For a few locations, adding the smoothed climatology of drought intensification as a predictor added skill to the model, thus it was also included even though for most regions this variable has zero weight. The cross-validated Brier Skill Score (BSS) for the 2-week drought intensification predictions is shown in Fig. 3a. For comparison, the BSS for the basic forward selection logistic regression model with 7 variables discussed earlier is shown in Fig. 3b. Most of the increased skill when using the new regression model is due to the USDM state prediction, which illustrates the value of converting the discrete USDM categories into a continuous distribution. Figure 4 shows several examples of the 2-week drought intensification predictions for the middle of July for recent drought years (2010-2013). Because the “observed” value of USDM intensification is a yes/no variable, the observed plots show two colors: orange for drought intensification and white for no intensification in the USDM. While general features in the observed and predicted USDM changes are similar, it is evident that these predictions are less skillful than the model estimates of the current drought state. Even so, it is encouraging to see that this empirical model is able to produce skillful drought intensification forecasts using only the current conditions and no forecast information.

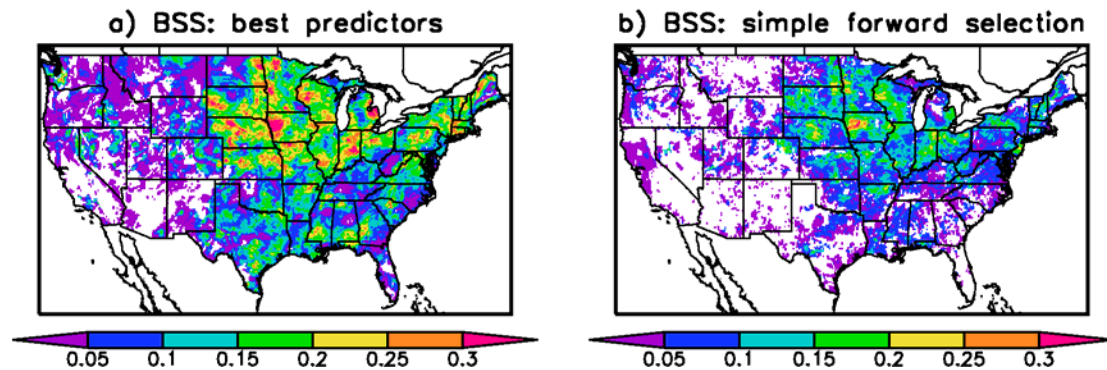


Figure 3: Brier skill scores (BSS) for two-week predictions of USDM-depicted drought intensification using the cross-validated optimized logistic regression model (left panel) and the basic forward selection logistic regression model (right panel), computed using all weekly forecasts from May-September for 2001-2014.

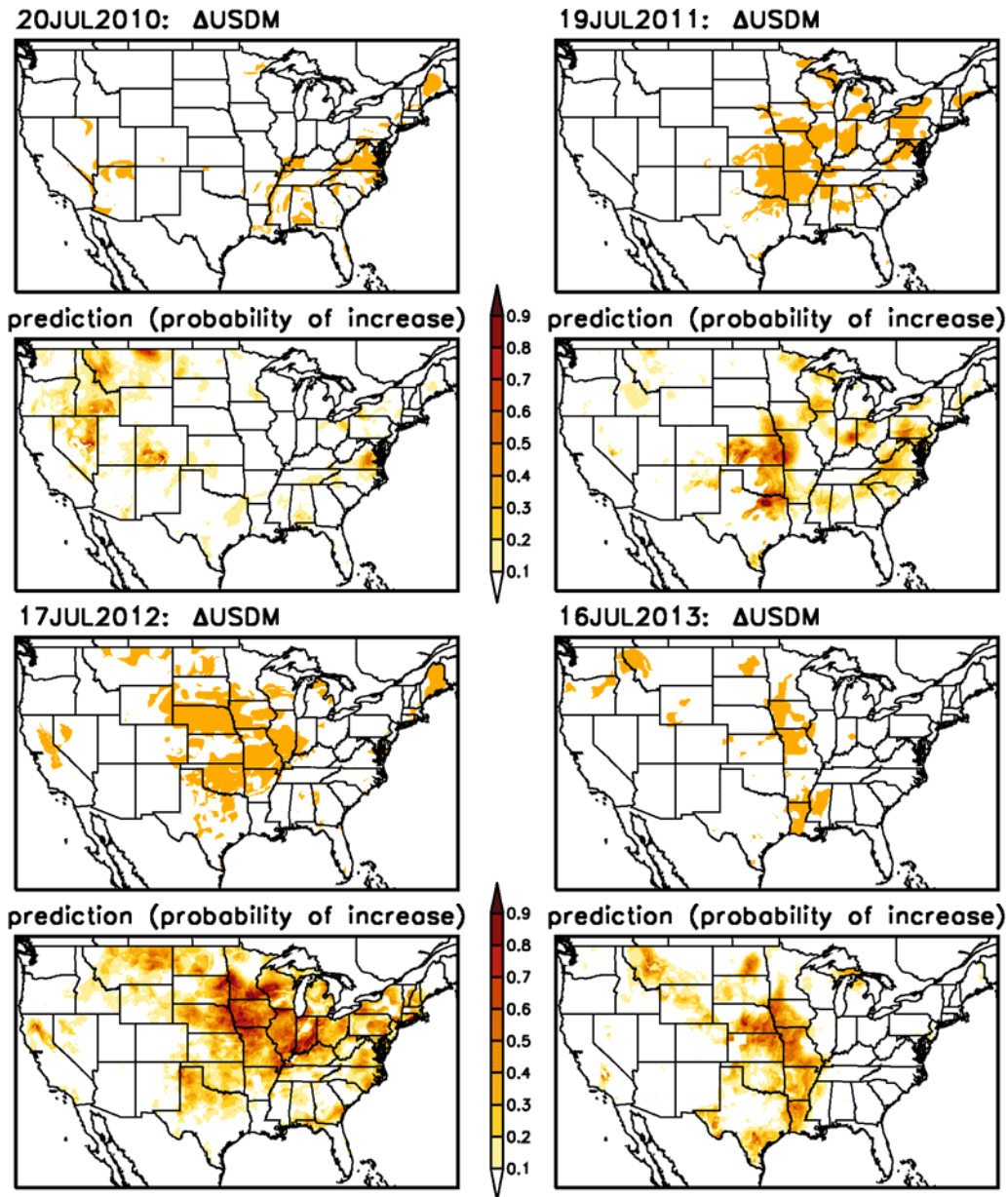


Figure 4: Observed and probabilistic predictions of 2-week changes in the USDM drought analysis for 20 July 2010 (upper left panels), 19 July 2011 (upper right panels), 17 July 2012 (lower left panels), and 16 July 2013 (lower right panels). The observed plots show orange for drought intensification and white for no intensification.

C) 2012 Central U.S. flash drought analysis

Late in the reporting period, we also started performing a detailed analysis of the flash drought event that impacted the central U.S. during the summer and fall of 2012. The primary goal of this part of the project is to assess changes in vegetation health and soil moisture conditions through a comparison of in situ, modeled, and observed datasets. This analysis will increase our understanding concerning the response of vegetation and soil moisture to flash drought onset and its subsequent evolution.

3. Highlights of accomplishments

- Supported ongoing efforts led by Co-I Hain to transition the ALEXI/ESI system from a research tool to a NOAA operational data product
- Developed a logistic regression model that uses the ESI, SPI, and NLDAS soil moisture datasets to estimate the current USDM state by converting the discrete USDM drought categories into a continuous function
- Developed a logistic regression model that uses the USDM state estimates along with the current values and temporal changes in the ESI, SPI, and NLDAS datasets to produce probabilistic drought intensification forecasts for the USDM over sub-seasonal time scales
- Evaluated and optimized the logistic regression models through cross-validation and an examination of individual case studies
- Started a new case study analysis of the 2012 flash drought over the central U.S. that will assess changes in vegetation health and soil moisture during the onset and development of the flash drought event

4. Future work

During the next twelve months, we will finalize the empirical models used to estimate the current USDM drought state and to predict future intensification in the USDM over sub-seasonal time scales. This includes testing other methods for regularization, such as LASSO (Tibshirani 1996) that may allow more variables to be used in a skillful manner. We will also assess whether including surrounding points (e.g. spatial smoothing) when computing the logistic regression fits reduces sampling noise and leads to more skillful forecasts. After finishing these tasks, we will use data from the Climate Forecasting System Reanalysis (CFSR) to examine relationships between meteorological variables and changes in the ESI and NLDAS datasets during drought and flash drought events. This will lead to additional insight into the typical evolution of flash drought from a soil moisture and vegetation health perspective. This information will also be used to assist efforts to develop synergistic methods that combine drought intensification forecasts from the logistic regression models with medium-range (0-3 months) temperature and precipitation forecasts from the National Multi-Model Ensemble (NMME). Last, we will also finish the analysis of the 2012 flash drought event across the central U.S.

5. Publications from the project

Otkin, J. A., D. Lorenz, M. Svoboda, C. Hain, and M. C. Anderson, 2015: Probabilistic drought intensification forecasts using empirical methods. In preparation for submission to *J. Hydrometeor.*

6. PI contact information

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7. Budget for upcoming year

Detailed Year 2 budget for the University of Wisconsin-Madison:

Year 2								
09/01/2015 - 08/31/2016								
I.	Labor and Fringe Benefits	Hours	Rate	Salary	Fringe %	Fringe	Cost	Totals
	J.Otkin - PI	150	53.13	\$ 7,969	34.5%	\$ 2,749	\$ 10,718	
	Post Doc - Res. Associate	1770	32.43	\$ 57,409	23.8%	\$ 13,663	\$ 71,072	
	Subtotal							\$81,790
II.	Travel							
	1 Trip / 2 people / 6 days / AMS Conference						3,385	
								3,385
III.	Materials and Supplies							1,014
IV.	Publication 15 pages @ \$145 each page							2,175
V.	University Indirect Cost at 53%							46,833
VI.	Equipment							7,803
	UW-MADISON YEAR 2 TOTAL							\$143,000

Combined Year 2 budget for all organizations:

Year 2 Budget Summary	
UW - Madison	\$ 143,000
U Nebraska - Lincoln	\$ 29,000
U Maryland - College Park	\$ 23,000
Total	\$ 195,000