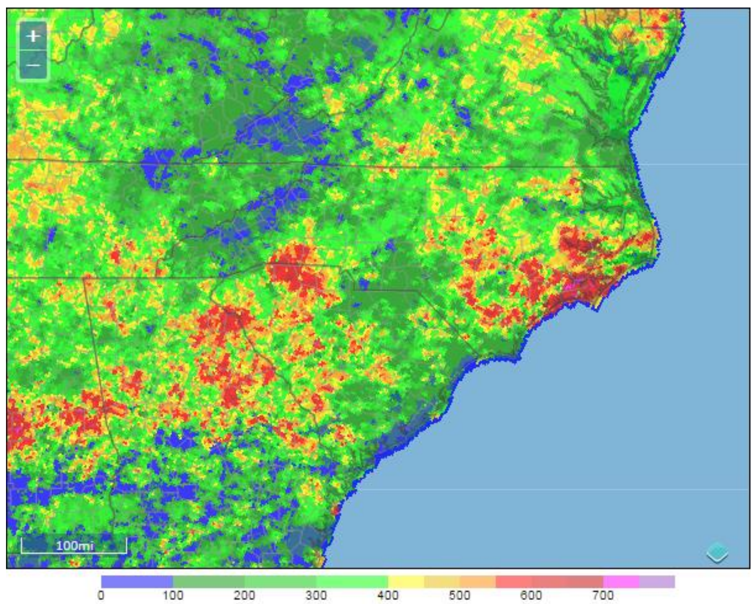
SUMMARY REPORT

Assessment of Indicators for Coastal Zone Fire Risk

Corey Davis, Rebecca Cumbie, and Ryan Boyles

State Climate Office of North Carolina

The organic soils in eastern North Carolina have a complex composition and are often found in regions with subtle but meaningful terrain differences. These soils can burn and smolder easily, even several feet underground. Because of this, existing measures of near-surface dryness and fire risk such as drought indices and National Fire Danger Rating System parameters have traditionally been viewed as poor indicators of fire and smoldering risk in organic soils. A further investigation of organic fire risk indicators was conducted as part of this NIDIS-funded project.



Gridded KBDI data for July 31, 2011

One commonly used fire risk parameter is the Keetch-Byram Drought Index (KBDI), which estimates dryness in the uppermost eight inches of the soil. KBDI has historically been available only at RAWS-standard weather stations, so much of eastern North Carolina did not have direct coverage. Using daily radar-derived precipitation estimates from the National Weather Service and daily maximum temperature and annual average precipitation data from the PRISM dataset, a gridded KBDI dataset was created at 4 km resolution for the period beginning in March 2007.

A comparison with the RAWS KBDI observations showed that the gridded data generally underestimates values, with annual maximum values 136.65 points lower in the gridded dataset, on average. This difference is likely due to the underestimation of maximum temperatures in the PRISM dataset and/or a warm bias in RAWS temperature observations.

Several gridded indices, including KBDI, daily precipitation, and the Standardized Precipitation Index (SPI) over one- to four-month periods, were then compared with fuel and soil moisture data from an experimental Estimated Smoldering Potential (ESP) dataset. This ESP data was collected intermittently from 2012 to 2014 from three coastal stations in the Pocosin Lakes National Wildlife

Refuge in Hyde County, in the Alligator River National Wildlife Refuge in Dare County, and near Green Swamp in Brunswick County. The results showed that all three indices were only weakly correlated with the ESP data. Separate comparisons using RAWS Energy Release Component (ERC) data using both fuel models G and O also showed only weak relationships with the soil moisture observations from the ERC dataset, as seen by the results in the table below.

	Alligator River (n = 349)	**Allen Road** (n = 278)	**Green Swamp** (n = 51)
Soil moisture vs. 1-month SPI	0.253	-0.075	0.833
Soil moisture vs. 2-month SPI	0.483	-0.235	0.725
Soil moisture vs. 3-month SPI	0.479	-0.316	0.648
Soil moisture vs. 4-month SPI	0.391	-0.352	0.711
Soil moisture vs. gridded daily precipitation	0.017	0.125	0.091
Soil moisture vs. gridded KBDI	0.372	-0.331	-0.563
Soil moisture vs. ERC (fuel model O)	-0.116	-0.057	-0.254
Soil moisture vs. ERC (fuel model G)	0.147	0.011	-0.217

Correlation coefficients (r) for analyses with soil moisture data from ESP arrays and other gridded and point-based datasets.

The weak correlations are likely because these indices cannot capture the terrain, drainage, and composition of organic soils. To that extent, few to no existing indices can model this combination of environmental and non-meteorological characteristics. Because of this, no single index based on current widely available data is likely to be a consistent indicator of organic fire risk. A combination of monitoring recent NFDRS parameters to assess surface fuel burning, local soil sampling, and groundwater levels is recommended until further improvements are made.

Additional research may suggest better options. A study in progress by Jim Reardon (Rocky Mountain Research Station) and Gary Curcio (Montgomery Community College Prescribed Fire Training Center) is examining remotely sensed soil moisture data as an indicator of smoldering in organic soils. The deployment of soil moisture probes across eastern North Carolina could also establish a reliable sensor network and provide a longer period of record than the ESP stations. Along with providing a finer-scale monitoring network in this part of the state, this would allow for a more robust comparison with existing datasets to search for good indicators of organic fire risk.

The gridded KBDI dataset should become a valuable monitoring tool, especially for assessing response and mop-up with lightning-caused fires, in non-organic regions since it provides local estimates between weather stations. Additional evaluation of temperature datasets may suggest a more accurate option than the daily PRISM data. If a daily relative humidity dataset was also found, gridded 100-hour and 1000-hour fuel moisture and ERC datasets could also be created.

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1. Introduction

Eastern North Carolina has a history of large and intense wildfires on both privately owned timberland and protected areas such as the Pocosin Lakes National Wildlife Refuge. Beneath the canopy of pines and Atlantic cedar trees, and under the shrubs, grasses, and litter lies a layer of soil rich with organic content that plays an important factor in the wildfire susceptibility and intensity across this region (Reardon and Curcio, 2011).

These organic soils, which reach depths of up to 12 feet in some parts of the slightly hilly pocosin region (Goodwin, 1989), can support long-lived and intense fires in the subsurface root zone. Because these fires can burn so deeply underground, measures of near-surface dryness and fire risk are often not useful for evaluating the risk of fire or smoldering in organic soils. For example, the Keetch-Byram Drought Index (KBDI) is an estimate of dryness only in the uppermost eight inches of soil, and has often been regarded as a poor indicator of coastal fire risk in North Carolina.

This project sought to further evaluate KBDI as a measure of coastal fire risk using a newly developed gridded KBDI dataset. Several other indices, including gridded precipitation, Standardized Precipitation Index, and Energy Release Component data, were also analyzed for their utility in assessing fire risk. An experimental Estimated Smoldering Potential dataset from three coastal sites provided fuel moisture data to serve as a proxy for fire or smoldering risk.

2. A Gridded KBDI Dataset

John Keetch and George Byram, fire scientists at the US Forest Service, developed their namesake drought index as a way to estimate the moisture deficit in the soils and duff. They established KBDI to have several characteristics that make it useful for fire risk monitoring. Its values vary continuously on a scale from 0 to 800, which gives an objective and detailed classification of local dryness. These values also correspond to the depth of dryness in the soil, where a value of 0 indicates no dryness and a value of 800 indicates dryness to a depth of eight inches (Keetch and Byram, 1968). Since KBDI is based on readily available weather parameters – the daily maximum temperature and total precipitation, and the annual average precipitation – it does not require sensors in the soil to make these estimates of the dryness.

The KBDI value changes daily based on the recent rainfall and maximum temperature, which provides a basic accounting of the moisture gained through precipitation while discounting runoff and moisture lost to evapotranspiration. Their KBDI model also follows a roughly sinusoidal annual pattern, reaching its annual minimum in the winter when fire risk is generally lowest and its maximum value in the summer.

Through the Weather Information Management System (WIMS) managed by the National Wildfire Coordinating Group, KBDI values are calculated each day for Remote Automatic Weather Stations (RAWS), which are used for local condition monitoring across the country. In 2012, the State Climate Office of North Carolina added additional stations including mesonet sites into WIMS for additional local fire risk monitoring purposes. However, there are still gaps between stations that can make it difficult to estimate true local fire risk, especially during the spring and summer when small-scale convective precipitation can be highly localized.

To ensure statewide availability of KBDI estimates, a gridded KBDI dataset was created using three components: daily precipitation data from the National Weather Service's radar-based and gauge-calibrated Advanced Hydrological Prediction Service (AHPS) dataset, and annual average precipitation and daily maximum temperature data from Oregon State's PRISM (Parameter-elevation Relationships on Independent Slopes Model) dataset. Both datasets are available for the continental United States at approximately 4 km spatial resolution.

Using the calculation steps first described by Keetch and Byram, then later summarized by Janis et al. (2002), gridded KBDI values were calculated since March 1, 2005, which represents a date when the eastern half of the country was relatively drought-free, thus justifying a starting KBDI value of zero. The analyses that follow used a start date of January 1, 2007, which gave additional spin-up time for the KBDI to go through two annual cycles, thereby adjusting to local differences in dryness during that time. An example of a daily gridded KBDI map is shown in Figure 2.1.

To provide a sense of error in the calculations, gridded KBDI values were compared to historical RAWS observations from the State Climate Office's Fire Weather Intelligence Portal. The station-based values were treated as the ground truth since they are manually verified by North Carolina Forest Service users in WIMS each day.

KBDI observations were available at 40 RAWS stations across North Carolina for the period from January 2007 through September 2014. Results of the comparison between the gridded and RAWS data are given in Table 2.1. The average correlation between the RAWS data and gridded KBDI data was $r = 0.778$, with a standard deviation of $\sigma = 0.066$. The main difference between datasets was a consistent underestimation of values in the gridded data compared to the RAWS data. The average difference between daily values was 115.13 points, and the average difference between annual maximum values was 136.65 points, with the RAWS data having higher values in both cases.

This cause of this discrepancy appears to be underestimation of the daily maximum temperatures in the PRISM dataset. At a representative group of five coastal RAWS stations that had an average daily KBDI difference of 115.75 points, the average difference between daily maximum temperature values was 0.8°C, with the RAWS temperatures being higher than the PRISM estimates. These differences affect the KBDI values most at higher temperatures because of the formulation of the KBDI Drought Factor calculation. An 0.8°C difference between the PRISM and RAWS maximum temperatures on a day with a maximum temperature of 20°C comparatively increases the daily Drought Factor, and the KBDI, by about 0.7 points. That difference occurring on 200 days, which is the approximate number of days with temperatures at or above 20°C each year, would constitute at least a 136 point difference in KBDI values.

Despite the differences in magnitudes between the gridded and RAWS KBDI data, both datasets showed similar overall patterns in values, so the gridded dataset should suffice for an initial comparison with the Estimated Smoldering Potential data. In the future, another dataset to estimate daily maximum temperatures could be identified and used instead of the PRISM data. One possible option is NOAA's Real-Time Mesoscale Analysis (RTMA) product, which is available on an hourly timescale. As such, it would require aggregation to determine the daily maximum, and even that could still miss the true high temperature by a degree or two. However, the RTMA dataset is higher resolution – 2.5 km rather than 4 km – and it appears to capture more of the local differences that are especially prominent on warm days, as the example in Figure 2.2 reveals. Another option worth exploring is the National Weather Service's Gridded Model Output Statistics (MOS), also available at 2.5 km resolution for the continental United States.

3. Fire Risk Indicators for Organic Soils

Assessing fire risk in organic soils can be challenging because the risk factors rarely go just skin-deep. Differences in terrain – the term 'pocosin' comes from an Algonquin word meaning "swamp on a hill" – affect the thickness and depth of the organic soil and root mat, and the fuel moisture also depends on groundwater levels. None of these attributes are directly captured by KBDI or other drought indices (LeQuire, 2010), so they have historically not been seen as good measures of fire or smoldering risk in organic soils.

There are few to no widespread ground-based measures of organic fire risk, such as fuel moisture sensors or probes, so finding a widely available existing index that is well-correlated with organic fuel moisture could provide useful insights about fire or smoldering risk even where no sensors are deployed.

To evaluate potential datasets as indicators of fire risk in organic soils, they were compared to data from several experimental Estimated Smoldering Potential (ESP) arrays installed by Jim Reardon with the Rocky Mountain Research Station and Gary Curcio, formerly with the NC Forest Service and now with the Montgomery Community College Prescribed Fire Training Center. This data was collected from three test sites across eastern North Carolina: one in the Alligator River National Wildlife Refuge in mainland Dare County, one off Allen Road in the Pocosin Lakes National Wildlife Refuge in Hyde County, and one in Green Swamp in Brunswick County. A map of the three array locations and pocosin habitats in coastal North Carolina is shown in Figure 3.1.

These three sites represent different local terrain and drainage: The Alligator River site is at low elevation and is considered a wet site, the Allen Road site is at higher elevation than the surrounding terrain and is considered a dry site, and the Green Swamp site is at moderate elevation compared to its surroundings.

Data from these sites was available from March 2012 through April 2014, with observations generally reported every two hours. Because of intermittent data transmission, none of the stations had a complete data record during this time period. The data availability for each site is summarized in Figure 3.2.

The parameters measured by each station included fuel moisture, soil moisture, and soil humidity (Reardon and Curcio, 2014). The fuel moisture data was measured by Campbell Scientific CS-505 electronic fuel sticks, typically mounted 12 inches above the forest floor. These sensors provide measures of surface fuel drying but not moisture content within in the soils themselves. The soil moisture data was monitored by Campbell Scientific CS-615 water content reflectometers within the muck soils. The soil humidity data was measured by several prototype sensors that were ultimately found to be unreliable estimates of root mat soil moisture.

The Estimated Smoldering Potential is based primarily on the local soil moisture content. ESP also depends on the local soil mineral content, but this value is essentially constant at each site and not an important factor in smoldering potential (Frandsen, 1997), making the fuel moisture content the critical variable.

At the Green Swamp site, earlier studies found the soil had an average root mat fuel moisture content of about 200% compared to the oven-dried sample weight (Reardon et al., 2007). Empirical evidence from prescribed burns suggested that burning when fuel moisture was at or above 180% – or 90% of the long-term average – was relatively safe against prolonged smoldering. Below 120% fuel moisture content – or 60% of the long-term average – burning was deemed to be high risk for sustained smoldering and costly mop-up (NC Forest Service, 2009).

Applying a similar logic to wildfires, it is reasonable to say that at low fuel moisture levels, the risk of a fire burning and smoldering in the root zone for prolonged periods is maximized, while at higher fuel moisture levels, the risk is lower. These guidelines served as the basis for this analysis.

For each ESP array, normalized fuel moisture and soil moisture values were calculated using the available data averaged over each day. These values effectively represent the percent of normal, and assuming a constant mineral content, they could be interpreted as smoldering or fire risk estimates as described above. The normalized fuel and soil moisture data were compared with several other datasets to assess their suitability as indicators of fire or smoldering risk.

3.1. SPI Analysis

The Standardized Precipitation Index (SPI) quantifies the frequency of precipitation during a given time period – often the past one month, two months, etc. – over that same period in past years, so it is useful for both short-term and long-term drought monitoring. Gridded SPI values on a daily timescale for periods ranging from one to four months were extracted for each ESP array location and compared to the daily normalized fuel and soil moisture.

The results of the fuel moisture vs. SPI analysis are shown in Table 3.1. There was no consistency among which time period showed the strongest correlation with the fuel moisture data, and the magnitudes of the correlation coefficients were low across the board; the strongest was $r = 0.389$ for a three-month SPI vs. normalized fuel moisture at the Green Swamp ESP Array.

The correlations with soil moisture data, shown in Table 3.2, were even more mixed. The Green Swamp site had high correlations ($r = 0.833$ for one-month SPI) but also a limited period of record ($n = 51$ days). The Allen Road site had negative correlations, and the Alligator River site had moderately positive ones. Ultimately, no useful connections could be made between SPI and either fuel moisture or soil moisture data.

3.2 Precipitation Analysis

Gridded precipitation data from the NWS AHPS dataset was extracted for each ESP array location at time lags of zero to five days in the past. The results of the fuel moisture vs. precipitation comparisons for each site are shown in Table 3.3. These correlations were slightly greater than with the SPI data, with a maximum value of $r = 0.438$ for the Green Swamp ESP Array. Correlations were greatest with a lag of zero days, or when considering precipitation falling on the same day as the fuel moisture was measured.

The correlations between the soil moisture and precipitation data are shown in Table 3.4. Correlations were lower than for the fuel moisture analysis and near zero in most cases, but they also did not drop off at non-zero time lags, suggesting that recent precipitation played a small role in influencing the local soil moisture.

3.3 KBDI Analysis

Gridded KBDI values were also extracted for each ESP array location at time lags of zero to five days in the past. The results when compared with the normalized fuel moisture data are shown in Table 3.5. Even the greatest correlations at a lag of zero days were low, with the maximum *r* values near -0.2. The Green Swamp site had non-negative correlations, implying that higher KBDI values – and more dryness – were associated with higher fuel moisture. This result may partially be due to a limited number of fuel moisture observations (n = 53) especially in the summertime, when KBDI values are highest.

Results of the normalized soil moisture vs. KBDI analysis are given in Table 3.6. Correlation coefficients for the Allen Road site were slightly more negative than for the fuel moisture analysis (r = -0.331 vs. r = -0.217), and the Green Swamp site showed the strongest correlation (r = -0.563), but the Alligator River site showed positive correlations with KBDI, which is again a non-intuitive finding.

3.4 ERC Analysis

The Energy Release Component (ERC) is a fire behavior parameter available from National Fire Danger Rating System (NFDRS) guidance in WIMS. It is commonly used for fire risk monitoring because it models the fuel load that may burn, particularly in larger and slower-drying fuels, if a fire starts. An ERC value multiplied by 25 gives the available energy in BTUs per square foot (Durango Interagency Dispatch, 2006). Like other NFDRS parameters, ERC is calculated using weather data inputs. In particular, ERC uses temperature, relative humidity, and precipitation data to model the drying in fuels.

ERC also depends on the fuel model being used. NFDRS offers 20 different fuel models that capture regional variations in vegetation and fuels. Fuel model G, which applies to dense conifer stands with heavy litter accumulation, is the most commonly used model in North Carolina. Many coastal sites also use fuel model O, which applies to pocosin regions with pine stands and brushlike fuels. The primary differences between these two models are the higher loading for the larger-diameter 100- and 1000-hour fuels in model G, a higher assumed heat content in BTUs per pound in model O, and a greater fuel bed depth – 4 feet vs. 1 foot – in model O (Bradshaw et al., 1983).

Because ERC is not currently available as a gridded dataset, data from the closest RAWS station to each ESP array was used. The closest station to the Alligator River ESP Array was the Dare Bomb Range RAWS site (NDBR), located 4.75 miles to the west. For the Allen Road ESP Array, the closest station was the Pocosin Lakes RAWS site (NPOC), located 5.05 miles to the north. And for the Green Swamp ESP Array, the Nature Conservancy RAWS site (NNAC), located 6.27 miles to the south, was used. A map of these site locations is given in Figure 3.3.

ERC data for both fuel models from all three RAWS stations was retrieved from WIMS and compared with the normalized fuel moisture data. The results are shown in Table 3.7. With a zero-day lag, the correlations were again maximized, and the magnitudes were the strongest of any analysis, all greater than 0.6. The correlations with fuel model O were slightly stronger than those with fuel model G for the Alligator River and Allen Road sites. At the Green Swamp site, fuel model G showed slightly higher correlations, but this may again be due to limited data availability (there were only 48 days with both ESP and ERC data) or local differences in soils. The ESP array on the northern edge of the Green Swamp is in an area of highly organic soils, while the Nature Conservancy RAWS site is in an area of more mineral-rich soils (Bucher and High, 2002).

Correlations between normalized soil moisture and RAWS ERC data are shown in Table 3.8. Compared to the fuel moisture analyses, the correlations were lower across the board; the maximum zero-day-lag correlation for any site was just $r = -0.254$ for the Green Swamp ESP Array. Correlations with fuel model G were non-negative for the Alligator River and Allen Road sites, which like the KBDI analysis does not match the expectations when comparing soil moisture to available energy.

Overall, the results of this analysis were consistent with findings by Reardon and Curcio (2014) that ERC and other NFDRS parameters do not closely reflect burning conditions in organic soils. In a set of research burns conducted under high ERC conditions, significant amounts of surface fuels burned, which is reflected by the strong correlations for the fuel moisture vs. ERC analysis. However, little to none of the organic soil was consumed during these burns, which matches the weak correlations from the soil moisture vs. ERC analysis.

4. Summary

The complex terrain, drainage, and composition of organic soils makes it difficult to assess the fire risk in those regions. Neither existing drought indices such as KBDI and SPI nor precipitation alone can fully capture these local impacts to fuel or soil moisture. When these indices miss the magnitude and timing of periods with heightened fire risk, as is sometimes the case with KBDI (LeQuire, 2010), it can have important implications for planning prescribed burns or allocating resources to potentially at-risk locations.

Another NFDRS parameter – the Energy Release Component – was found to be well-correlated with surface fuel moisture. For these surface fuels, ERC is recommended as a good indicator of fire risk. Fuel model O is optimal as it most closely fits the soil and vegetation characteristics of this region, but fuel model G also correlates well with observed fuel moisture values. Monitoring for surface burning will also be improved with the new gridded KBDI dataset, which fills in gaps between existing RAWS stations, such as those shown in Figure 4.1, providing estimates where there is currently no coverage. This gridded KBDI dataset could be improved with a more accurate gridded temperature dataset, and if a gridded relative humidity dataset was also identified, a gridded ERC dataset could be created.

However, ERC was not strongly correlated with organic soil moisture collected from three experimental ESP arrays, which confirmed past findings that NFDRS parameters cannot capture the complexities in organic soils. Non-meteorological factors such as groundwater levels and local terrain also play an important role in influencing local burning and smoldering conditions. Because of this, no single index based on current widely available data is likely to be a consistent indicator of organic fire risk. A combination of monitoring recent NFDRS parameters to assess surface fuel burning, local soil sampling, and groundwater levels is recommended until further improvements are made. One study, currently in progress, is examining remotely sensed soil moisture data as an indicator of smoldering in organic soils (Reardon and Curcio, 2014).

Deployment of additional soil moisture probes across eastern North Carolina could also provide monitoring information, although this would still leave gaps between stations without relevant guidance. However, establishing a reliable and accurate network of soil moisture sensors could eventually provide a sufficiently long period of record to cover several wet and dry periods. This would allow for a more robust analysis than was possible with the limited ESP station data. Past research at the State Climate Office has also linked experimental sensor data, such as leaf wetness observations, with more widely available fields such as relative humidity. Although organic fire risk has many more inputs than atmospheric moisture alone, having several years of observations from multiple sites could help identify these potential inputs, particularly for periods of high fire or smoldering risk.

Although they are not useful indicators of organic fire risk, it is possible that KBDI, ERC, and other drought or fire risk parameters are good indicators of other non-climatic environmental phenomena, such as estuarine salinity and dissolved oxygen content. Similar to organic soil moisture and smoldering potential, ground-based observations of these parameters are limited, so identifying more widely available datasets that correlate well with these features would provide valuable insights to anyone researching or monitoring coastal water conditions. Additional studies and research with regional partners could help identify the knowledge gaps and needs in these areas.

Acknowledgements

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Table 2.1: Results of the comparison between KBDI data from the gridded dataset and 40 RAWS stations across North Carolina.

Station	RAWS vs. Gridded Correlation	Avg. Difference Between Daily Values (Gridded - RAWS)	Avg. Difference Between Annual Maximum Values (Gridded - RAWS)	Number of Observations
N7MR	0.716	-135.99	-187.33	2676 (94.6%)
NBUS	0.644	-93.94	-241.93	2807 (99.2%)
NCHE	0.731	-121.30	-193.42	2510 (88.7%)
NCOW	0.751	-186.33	-288.25	2280 (80.6%)
NDAV	0.714	-79.44	-129.26	2655 (93.8%)
NGRF	0.804	-95.34	-163.62	2816 (99.5%)
NGUI	0.814	-73.28	-91.73	2489 (88%)
NHIG	0.646	-86.63	-235.06	2750 (97.2%)
NJCY	0.691	-206.14	-281.51	2758 (97.5%)
NNCP	0.774	-88.87	-118.68	2434 (86%)
NRUT	0.826	-106.36	-101.02	2718 (96%)
NTUS	0.834	-91.57	-119.04	2755 (97.3%)
NWAY	0.675	-46.34	-133.99	2455 (86.7%)
NRAV	0.820	-97.31	-161.64	2578 (91.1%)
NREN	0.803	-104.18	-159.95	2687 (94.9%)
NCAS	0.899	-92.47	-103.11	2730 (96.5%)
NDUK	0.904	-84.79	-59.97	2815 (99.5%)
NLEX	0.763	-161.25	-199.50	2814 (99.4%)
NTYL	0.821	-50.83	-81.79	2727 (96.4%)
NBAC	0.738	-145.48	-80.31	2755 (97.3%)
NDRO	0.738	-171.88	-169.34	2749 (97.1%)
NFBR	0.773	-140.61	-146.17	2822 (99.7%)
NHOF	0.756	-95.08	-46.82	2717 (96%)
NMTI	0.810	-136.20	-134.50	2787 (98.5%)
NNAC	0.864	-105.87	-39.82	2752 (97.2%)
NRCK	0.723	-179.42	-129.08	2681 (94.7%)
NSND	0.745	-116.36	-105.12	2787 (98.5%)
NSUN	0.862	-75.33	-37.43	2760 (97.5%)
NTUR	0.829	-133.21	-103.80	2783 (98.3%)
NUWH	0.866	-106.20	-144.89	2736 (96.7%)
NWHI	0.807	-127.75	-103.55	2731 (96.5%)
NBFT	0.753	-170.51	-147.68	2644 (93.4%)
NCRN	0.648	-83.85	-106.74	2644 (93.4%)
NDBR	0.740	-130.83	-213.35	2390 (84.5%)
NELI	0.790	-121.57	-143.60	2740 (96.8%)
NFAI	0.796	-66.51	-60.55	2762 (97.6%)
NFIN	0.766	-178.91	-178.65	2707 (95.7%)
NGRC	0.842	-118.68	-127.57	2757 (97.4%)
NNWB	0.823	-101.88	-88.44	2783 (98.3%)
NPOC	0.823	-96.57	-107.90	2814 (99.4%)
Average	0.778	-115.13	-136.65	2693.9 (95.2%)

Figure 2.1: Gridded KBDI data for July 31, 2011.

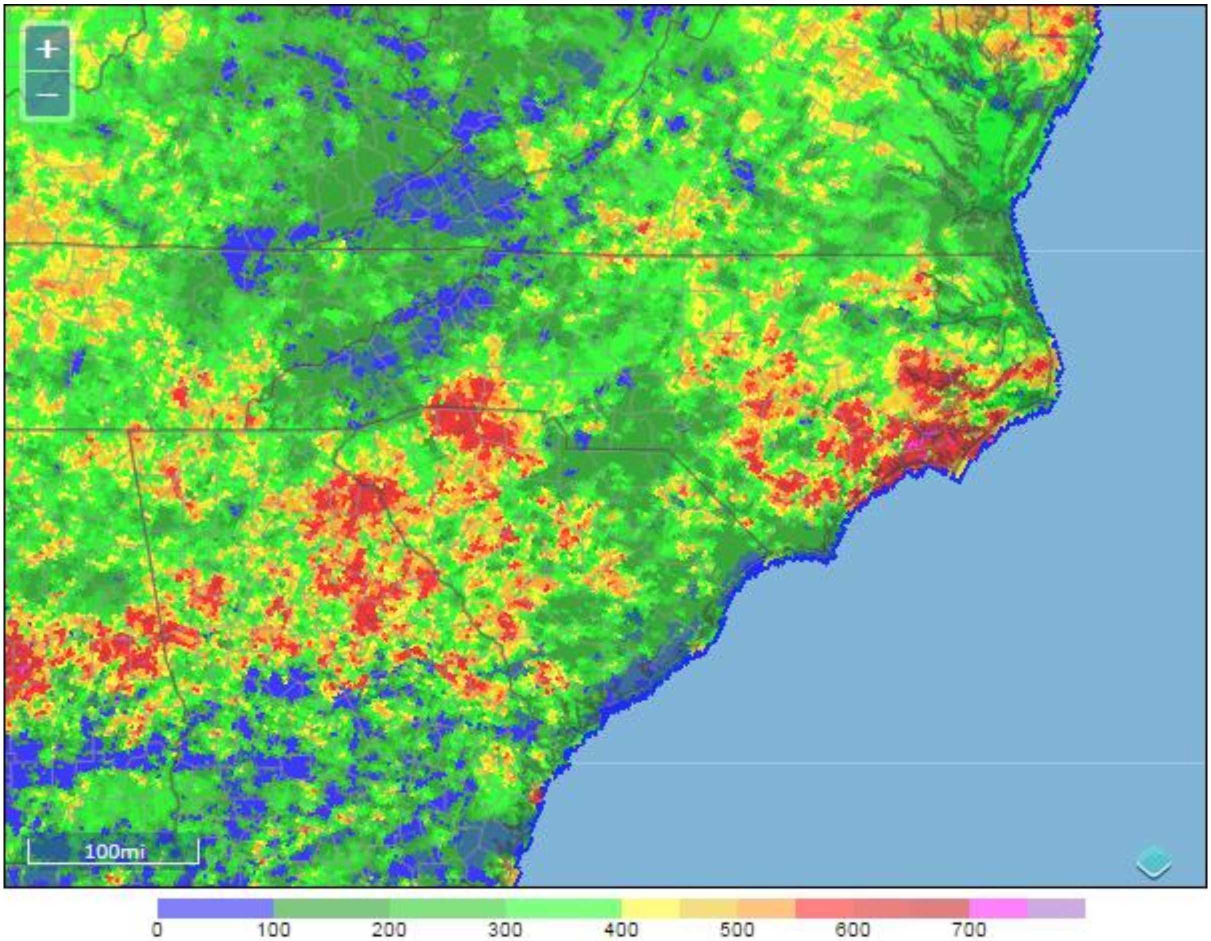

Figure 2.2: Comparison of PRISM daily maximum temperatures (left) and RTMA 1800 UTC temperatures (right) on June 30, 2015.

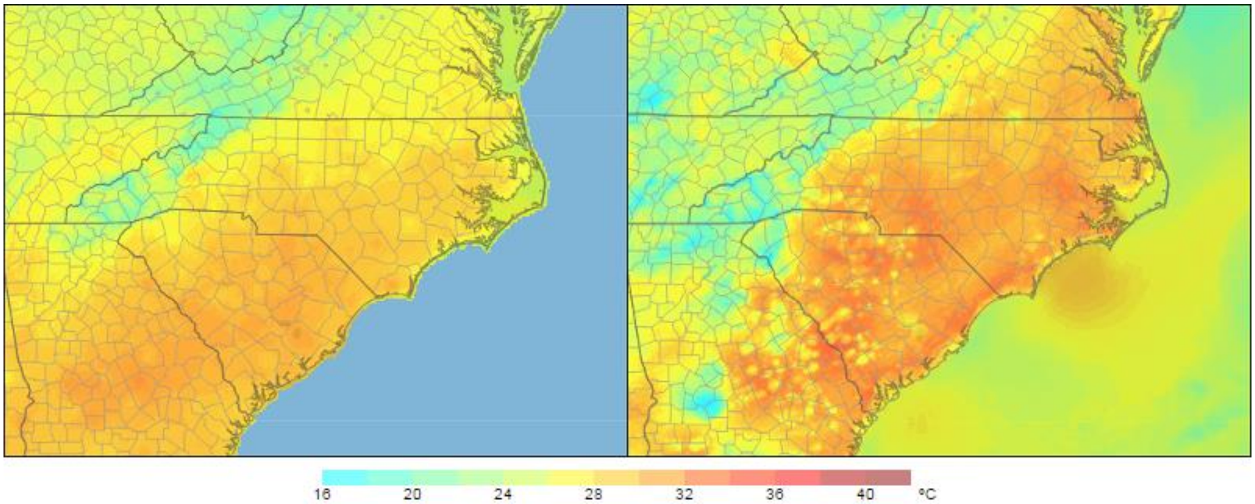

Table 3.1: Correlations for the normalized fuel moisture vs. daily SPI analysis.

Alligator River ESP Array (*n* =349)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. 1-month SPI	0.160
Normalized Fuel Moisture vs. 2-month SPI	0.138
Normalized Fuel Moisture vs. 3-month SPI	0.197
Normalized Fuel Moisture vs. 4-month SPI	0.205

Allen Road ESP Array (*n* =310)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. 1-month SPI	0.119
Normalized Fuel Moisture vs. 2-month SPI	-0.020
Normalized Fuel Moisture vs. 3-month SPI	-0.079
Normalized Fuel Moisture vs. 4-month SPI	-0.109

Green Swamp ESP Array (*n* =53)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. 1-month SPI	-0.044
Normalized Fuel Moisture vs. 2-month SPI	0.366
Normalized Fuel Moisture vs. 3-month SPI	0.389
Normalized Fuel Moisture vs. 4-month SPI	0.241

Table 3.2: Correlations for the normalized soil moisture vs. daily SPI analysis.

Alligator River ESP Array (n =349)

Comparison	Correlation Coefficient r
Normalized Soil Moisture vs. 1-month SPI	0.253
Normalized Soil Moisture vs. 2-month SPI	0.483
Normalized Soil Moisture vs. 3-month SPI	0.479
Normalized Soil Moisture vs. 4-month SPI	0.391

Allen Road ESP Array (n =278)

Comparison	Correlation Coefficient r
Normalized Soil Moisture vs. 1-month SPI	-0.075
Normalized Soil Moisture vs. 2-month SPI	-0.235
Normalized Soil Moisture vs. 3-month SPI	-0.316
Normalized Soil Moisture vs. 4-month SPI	-0.352

Green Swamp ESP Array (n =51)

Comparison	Correlation Coefficient r
Normalized Soil Moisture vs. 1-month SPI	0.833
Normalized Soil Moisture vs. 2-month SPI	0.725
Normalized Soil Moisture vs. 3-month SPI	0.648
Normalized Soil Moisture vs. 4-month SPI	0.711

Table 3.3: Correlations for the normalized fuel moisture vs. daily NWS AHPS precipitation analysis.

Alligator River ESP Array (*n* =349)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. Precip. (0 day lag)	0.348
Normalized Fuel Moisture vs. Precip. (1 day lag)	0.171
Normalized Fuel Moisture vs. Precip. (2 day lag)	0.055
Normalized Fuel Moisture vs. Precip. (3 day lag)	0.059
Normalized Fuel Moisture vs. Precip. (4 day lag)	0.041
Normalized Fuel Moisture vs. Precip. (5 day lag)	0.071

Allen Road ESP Array (*n* =310)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. Precip. (0 day lag)	0.412
Normalized Fuel Moisture vs. Precip. (1 day lag)	0.120
Normalized Fuel Moisture vs. Precip. (2 day lag)	0.011
Normalized Fuel Moisture vs. Precip. (3 day lag)	-0.007
Normalized Fuel Moisture vs. Precip. (4 day lag)	-0.073
Normalized Fuel Moisture vs. Precip. (5 day lag)	-0.145

Green Swamp ESP Array (*n* =53)

Comparison	Correlation Coefficient *r*
Normalized Fuel Moisture vs. Precip. (0 day lag)	0.438
Normalized Fuel Moisture vs. Precip. (1 day lag)	0.258
Normalized Fuel Moisture vs. Precip. (2 day lag)	-0.043
Normalized Fuel Moisture vs. Precip. (3 day lag)	-0.180
Normalized Fuel Moisture vs. Precip. (4 day lag)	-0.190
Normalized Fuel Moisture vs. Precip. (5 day lag)	0.069

Table 3.4: Correlations for the normalized soil moisture vs. daily NWS AHPS precipitation analysis.

Alligator River ESP Array (*n* =349)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. Precip. (0 day lag)	0.017
Normalized Soil Moisture vs. Precip. (1 day lag)	0.012
Normalized Soil Moisture vs. Precip. (2 day lag)	0.026
Normalized Soil Moisture vs. Precip. (3 day lag)	0.028
Normalized Soil Moisture vs. Precip. (4 day lag)	0.049
Normalized Soil Moisture vs. Precip. (5 day lag)	0.065

Allen Road ESP Array (*n* =278)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. Precip. (0 day lag)	0.125
Normalized Soil Moisture vs. Precip. (1 day lag)	0.108
Normalized Soil Moisture vs. Precip. (2 day lag)	0.100
Normalized Soil Moisture vs. Precip. (3 day lag)	0.097
Normalized Soil Moisture vs. Precip. (4 day lag)	0.018
Normalized Soil Moisture vs. Precip. (5 day lag)	-0.079

Green Swamp ESP Array (*n* =51)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. Precip. (0 day lag)	0.091
Normalized Soil Moisture vs. Precip. (1 day lag)	0.161
Normalized Soil Moisture vs. Precip. (2 day lag)	0.248
Normalized Soil Moisture vs. Precip. (3 day lag)	0.269
Normalized Soil Moisture vs. Precip. (4 day lag)	0.187
Normalized Soil Moisture vs. Precip. (5 day lag)	0.304

Table 3.5: Correlations for the normalized fuel moisture vs. daily gridded KBDI analysis.

Alligator River ESP Array (n =349)

Comparison	Correlation Coefficient r
Normalized Fuel Moisture vs. KBDI (0 day lag)	-0.203
Normalized Fuel Moisture vs. KBDI (1 day lag)	-0.067
Normalized Fuel Moisture vs. KBDI (2 day lag)	0.012
Normalized Fuel Moisture vs. KBDI (3 day lag)	0.041
Normalized Fuel Moisture vs. KBDI (4 day lag)	0.052
Normalized Fuel Moisture vs. KBDI (5 day lag)	0.043

Allen Road ESP Array (n =310)

Comparison	Correlation Coefficient r
Normalized Fuel Moisture vs. KBDI (0 day lag)	-0.217
Normalized Fuel Moisture vs. KBDI (1 day lag)	-0.118
Normalized Fuel Moisture vs. KBDI (2 day lag)	-0.088
Normalized Fuel Moisture vs. KBDI (3 day lag)	-0.061
Normalized Fuel Moisture vs. KBDI (4 day lag)	-0.038
Normalized Fuel Moisture vs. KBDI (5 day lag)	-0.041

Green Swamp ESP Array (n =53)

Comparison	Correlation Coefficient r
Normalized Fuel Moisture vs. KBDI (0 day lag)	0.234
Normalized Fuel Moisture vs. KBDI (1 day lag)	0.279
Normalized Fuel Moisture vs. KBDI (2 day lag)	0.320
Normalized Fuel Moisture vs. KBDI (3 day lag)	0.311
Normalized Fuel Moisture vs. KBDI (4 day lag)	0.280
Normalized Fuel Moisture vs. KBDI (5 day lag)	0.209

Table 3.6: Correlations for the normalized soil moisture vs. daily gridded KBDI analysis.

Alligator River ESP Array (*n* =349)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. KBDI (0 day lag)	0.372
Normalized Soil Moisture vs. KBDI (1 day lag)	0.356
Normalized Soil Moisture vs. KBDI (2 day lag)	0.332
Normalized Soil Moisture vs. KBDI (3 day lag)	0.309
Normalized Soil Moisture vs. KBDI (4 day lag)	0.300
Normalized Soil Moisture vs. KBDI (5 day lag)	0.285

Allen Road ESP Array (*n* =278)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. KBDI (0 day lag)	-0.331
Normalized Soil Moisture vs. KBDI (1 day lag)	-0.306
Normalized Soil Moisture vs. KBDI (2 day lag)	-0.289
Normalized Soil Moisture vs. KBDI (3 day lag)	-0.272
Normalized Soil Moisture vs. KBDI (4 day lag)	-0.255
Normalized Soil Moisture vs. KBDI (5 day lag)	-0.254

Green Swamp ESP Array (*n* =51)

Comparison	Correlation Coefficient *r*
Normalized Soil Moisture vs. KBDI (0 day lag)	-0.563
Normalized Soil Moisture vs. KBDI (1 day lag)	-0.542
Normalized Soil Moisture vs. KBDI (2 day lag)	-0.513
Normalized Soil Moisture vs. KBDI (3 day lag)	-0.475
Normalized Soil Moisture vs. KBDI (4 day lag)	-0.437
Normalized Soil Moisture vs. KBDI (5 day lag)	-0.400

Table 3.7: Correlations for the normalized fuel moisture vs. daily station-based ERC analyses.

Alligator River ESP Array (n =344)

ERC data from the Dare Bomb Range RAWS site (NDBR)

Comparison	Correlation Coefficient r with Fuel Model O	Correlation Coefficient r with Fuel Model G
Normalized Fuel Moisture vs. ERC (0 day lag)	-0.739	-0.614
Normalized Fuel Moisture vs. ERC (1 day lag)	-0.561	-0.390
Normalized Fuel Moisture vs. ERC (2 day lag)	-0.325	-0.219
Normalized Fuel Moisture vs. ERC (3 day lag)	-0.237	-0.152
Normalized Fuel Moisture vs. ERC (4 day lag)	-0.197	-0.125
Normalized Fuel Moisture vs. ERC (5 day lag)	-0.176	-0.097

Allen Road ESP Array (n =280)

ERC data from the Pocosin Lakes RAWS site (NPOC)

Comparison	Correlation Coefficient r with Fuel Model O	Correlation Coefficient r with Fuel Model G
Normalized Fuel Moisture vs. ERC (0 day lag)	-0.673	-0.664
Normalized Fuel Moisture vs. ERC (1 day lag)	-0.390	-0.323
Normalized Fuel Moisture vs. ERC (2 day lag)	-0.125	-0.081
Normalized Fuel Moisture vs. ERC (3 day lag)	-0.130	-0.091
Normalized Fuel Moisture vs. ERC (4 day lag)	-0.076	-0.057
Normalized Fuel Moisture vs. ERC (5 day lag)	0.039	-0.028

Green Swamp ESP Array (n =48)

ERC data from the Nature Conservancy RAWS site (NNAC)

Comparison	Correlation Coefficient r with Fuel Model O	Correlation Coefficient r with Fuel Model G
Normalized Fuel Moisture vs. ERC (0 day lag)	-0.650	-0.769
Normalized Fuel Moisture vs. ERC (1 day lag)	-0.415	-0.824
Normalized Fuel Moisture vs. ERC (2 day lag)	-0.257	-0.739
Normalized Fuel Moisture vs. ERC (3 day lag)	-0.061	-0.114
Normalized Fuel Moisture vs. ERC (4 day lag)	0.074	-0.581
Normalized Fuel Moisture vs. ERC (5 day lag)	0.146	0.080

Table 3.8: Correlations for the normalized soil moisture vs. daily station-based ERC analyses.

Alligator River ESP Array (*n* =344)

ERC data from the Dare Bomb Range RAWS site (NDBR)

Comparison	Correlation Coefficient *r* with Fuel Model O	Correlation Coefficient *r* with Fuel Model G
Normalized Soil Moisture vs. ERC (0 day lag)	-0.116	0.147
Normalized Soil Moisture vs. ERC (1 day lag)	-0.056	0.155
Normalized Soil Moisture vs. ERC (2 day lag)	-0.050	0.142
Normalized Soil Moisture vs. ERC (3 day lag)	-0.053	0.163
Normalized Soil Moisture vs. ERC (4 day lag)	-0.105	0.067
Normalized Soil Moisture vs. ERC (5 day lag)	-0.084	0.104

Allen Road ESP Array (*n* =252)

ERC data from the Pocosin Lakes RAWS site (NPOC)

Comparison	Correlation Coefficient *r* with Fuel Model O	Correlation Coefficient *r* with Fuel Model G
Normalized Soil Moisture vs. ERC (0 day lag)	-0.057	0.011
Normalized Soil Moisture vs. ERC (1 day lag)	-0.109	0.001
Normalized Soil Moisture vs. ERC (2 day lag)	-0.123	0.035
Normalized Soil Moisture vs. ERC (3 day lag)	-0.102	0.058
Normalized Soil Moisture vs. ERC (4 day lag)	-0.095	0.078
Normalized Soil Moisture vs. ERC (5 day lag)	-0.046	0.126

Green Swamp ESP Array (*n* =46)

ERC data from the Nature Conservancy RAWS site (NNAC)

Comparison	Correlation Coefficient *r* with Fuel Model O	Correlation Coefficient *r* with Fuel Model G
Normalized Soil Moisture vs. ERC (0 day lag)	-0.254	-0.217
Normalized Soil Moisture vs. ERC (1 day lag)	-0.395	-0.266
Normalized Soil Moisture vs. ERC (2 day lag)	-0.401	-0.343
Normalized Soil Moisture vs. ERC (3 day lag)	-0.375	-0.411
Normalized Soil Moisture vs. ERC (4 day lag)	-0.295	-0.347
Normalized Soil Moisture vs. ERC (5 day lag)	-0.333	-0.446

Figure 3.1: Pocosin habitats (red) in eastern North Carolina, and the locations of the Alligator River ESP Array (AR), Pocosin Lakes/Allen Road ESP Array (PL), and the Green Swamp ESP Array (GS). Map taken from NCGAP 1992.

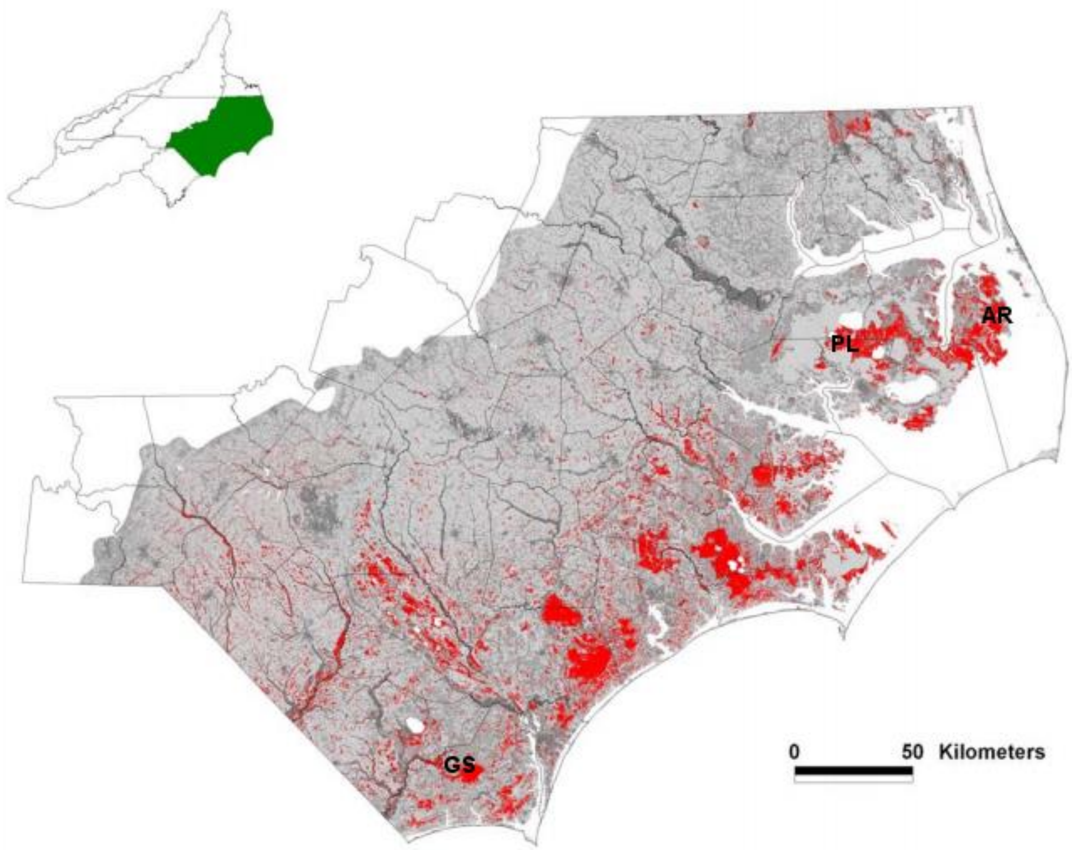

Figure 3.2: Data availability (in green) for each ESP array.

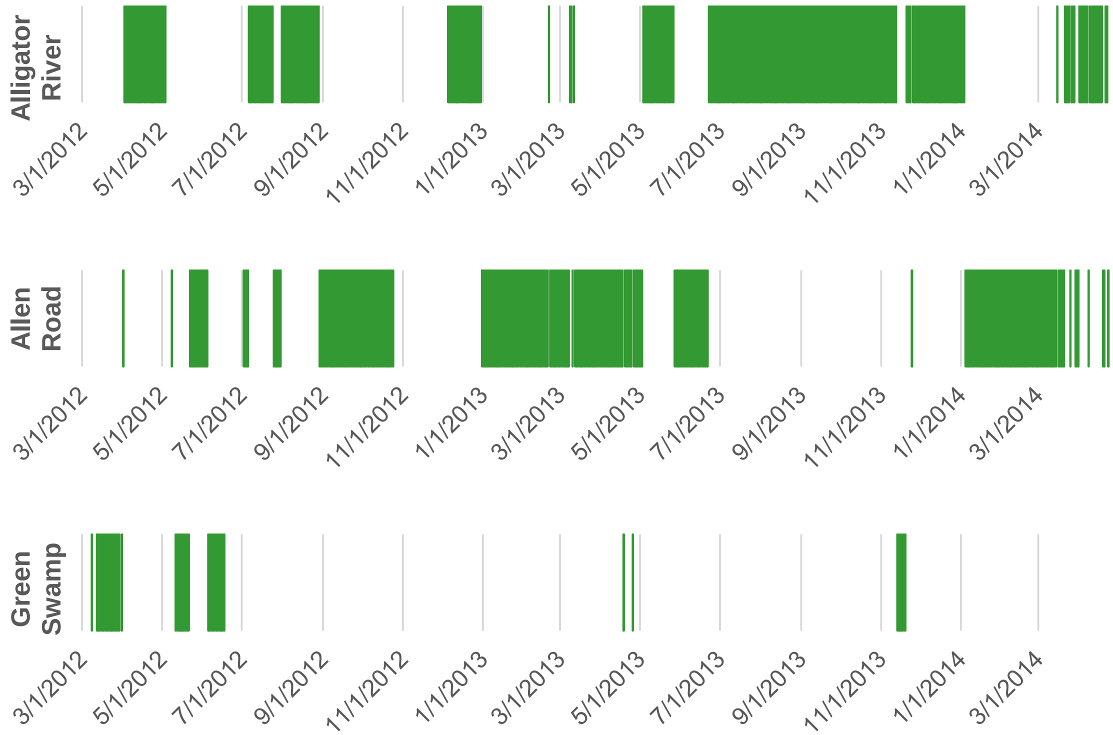

Figure 3.3: Locations of ESP arrays (green) and nearby RAWS stations (red) in eastern North Carolina. Base map data from Google Earth.

Figure 4.1: KBDI values on June 31, 2011, interpolated from observations from the RAWS stations indicated by black triangles. The difference in local resolution is apparent by comparing with Figure 2.1.