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Near-real time mapping of Keetch-Byram drought index in the south-eastern United States

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This paper is derived from a presentation at the 4th Fire and Forest Meteorology Conference, Reno, NV, USA, held 13–15 November 2001

Abstract. High spatial resolution maps of daily Keetch-Byram Drought Index (KBDI) are constructed for the south-eastern United States. KBDI is a cumulative algorithm for estimating fire potential from meteorological information, including daily maximum temperature, daily total precipitation, and mean annual precipitation. With few input parameters, the KBDI is attractive for providing estimates of fire potential at a large number of locations. The Southeast Regional Climate Center (SERCC) applies the original algorithms over daily time steps to maximize the response time in the event of rapidly increasing fire potential. Algorithms are applied to a network of 261 weather stations across the south-eastern United States to provide regional contour maps of KBDI as well as maps of week-to-week KBDI difference. Though uniformity and spatial density of weather stations and the consistency of input parameters are potential hurdles, it is shown that careful compilation of meteorological databases makes KBDI a tractable and valuable monitoring tool for automated fire-potential monitoring.

Additional keywords: fire potential; meteorological parameters; drought.

Introduction

A conventional tool for estimating fire potential is the Keetch-Byram Drought Index (KBDI). Since 1996, the National Interagency Fire Center has produced daily KBDI maps for the United States with somewhat coarse spatial coverage of input parameters in the eastern United States (USDA 2002). A near-real-time calculation and mapping of KBDI has been developed and used operationally in the south-eastern United States (Johnson and Forthun 2001). This development overcomes some limitations in drought and fire potential indices. Specifically, some indices or applications thereof lack the temporal precision to detect the inception and abatement of fire and drought hazards (Byun and Wilhite 1999). Other indices applied at spatially coarse resolutions may reflect fire potential only over broad geographical areas (Hatton *et al.* 1998). The purpose of this paper is to describe a process for calculating KBDI at daily time steps over a dense network of weather stations in the south-eastern United States. Index calculations and mapping techniques detail the usefulness of KBDI for reacting quickly to changing moisture conditions and providing fire potential assessments where limited meteorological information is available.

Background

Several indices have been developed to monitor a variety of scales, types, and impacts of drought and moisture deficiency (see Heim 2000 or Byun and Wilhite 1999 for reviews of drought indices). The KBDI is a cumulative estimate of fire potential (moisture deficiency) based on meteorological input parameters and an empirical approximation for moisture depletion in the upper soil and surface litter levels (Keetch and Byram 1968). Requiring only the readily accessible meteorological parameters of maximum daily temperature, daily precipitation, and the normal precipitation, KBDI should be viewed as an early warning tool for fire potential and severity.

KBDI is an expression of moisture deficiency relative to 20.32 cm (8 inches) of water as field capacity and ranges from zero for saturated soil and surface litter (i.e. no drought) to 800 units for acute moisture depletion (i.e. extreme drought). In addition to numerical values, KBDI can be

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Table 1. General description of moisture conditions and fire potential for relative KBDI levels (SERCC 2002; USDA 2002)

KBDI range	General description
0–150	Upper soil and surface litter are wet. Fire potential is minimal.
150–300	Upper soil and surface litter are moist and do not contribute to fire intensity. Some surface litter remains damp and undisturbed following a fire. Fire behavior is predictable.
300–500	Upper soil and surface litter are dry and may contribute to fire intensity. Fire consumes most surface litter along with a significant loss in organic soil material. Although escaped fire is difficult to control, fire behavior is somewhat predictable.
500–700	Upper soil and surface litter are very dry. Above 600 is associated with severe drought. Surface litter and organic soil material contribute to fire intensity. All surface litter and most of the organic layer are consumed by fire leaving excessive site damage. Above 600, fire suppression is a significant undertaking.
700–800	Upper soil and surface litter are extremely dry. Live understory vegetation burns actively and contributes to fire potential. Fire behavior is unpredictable with crowning and downwind spotting. Associated with extreme drought and increased wildfire occurrence.

related to a five-stage descriptive fire-potential scale (Table 1). KBDI has been applied in a wide variety of environments, including the upper mid-western and south-eastern United States (Lorimer and Gough 1988), south-eastern Australia (Hatton *et al.* 1998), and Malaysia (Livingston 1974). The KBDI is likely more representative in the south-eastern United States and similar climates with 20.32 cm of soil capacity.

KBDI calculations

Initializing the KBDI

Since KBDI is a cumulative fire potential/moisture deficiency index, calculations may be initialized when KBDI is assumed to be zero. To minimize disparity between litter and soil moisture, KBDI should be initialized when the soil is near saturation. Soil saturation varies by geographic region but may be reached during prolonged precipitation events. A method for initializing the KBDI is to identify periods of rainfall events that bring soils close to field capacity. Keetch and Byram (1968) suggested 15–20 cm of precipitation in one week was sufficient for initialization. For most locations in the south-eastern United States, KBDI calculations are initialized in 1997 or 1998. Climatic regions that do not typically meet initialization criteria may be less suited for KBDI as a monitoring tool.

Calculating the KBDI

Limited numbers of weather observations are required to compute the KBDI, including daily maximum temperature and daily total precipitation. Average annual total precipitation is incorporated in an exponential equation to approximate the rate of evapotranspiration or moisture loss from a vegetated area. This equation approximates the relationship between moisture loss from soil and leaf litter by using mean annual precipitation as a surrogate for vegetation density. The assumption is that vegetation density is determined by the average moisture availability. Areas with higher annual total precipitation will have a greater vegetation density and therefore a greater rate of transpiration. To maintain high transpiration rates during periods of precipitation deficiency, areas of greater vegetation density will deplete soil moisture more readily. Although *median* annual precipitation may be more appropriate than *mean* annual precipitation, this assertion has not undergone testing. The efficacy of annual precipitation in place of evapotranspiration is unknown, especially as seasonal climates diverge from those of the south-eastern United States.

The exponential relationship for determining a drought factor (*DF*) for time *t* is given by:

$$DF_t = \frac{\left(800 - KBDI_{t-1}\right)\left(0.968\,e^{0.0875\,TMAX_t + 1.5552} - 8.30\right)\times 10^{-3}}{1 + 10.88\,e^{-0.0174\,R}}, \tag{1}$$

where $TMAX_t$ is daily maximum temperature (°C), R is mean annual rainfall (cm), and $KBDI_{t-1}$ is the Keetch-Byram Drought Index for time t–1 (Keetch and Byram 1968; Alexander 1992). Drought factor is measured in hundredths of inches (as is KBDI) and represents the change in moisture availability over a time step. Though equation (1) has been modified for input of parameters in SI units, DF and KBDI retain English units to maintain consistency and familiarity with other fire potential measures used in the United States and elsewhere.

General rules for *DF* calculations are based on temperature and precipitation thresholds. Keetch and Byram (1968) created look-up tables for *DF* over fixed temperature ranges with 10°C (50°F) as the lower bound. A quick examination of equation (1) identifies 6.78°C as a limiting case; thus, *DF* is zero when daily maximum temperature is less than 6.78°C. When daily maximum temperature is greater than 6.78°C, *DF* increases exponentially. Dry-bulb temperature at time of daily observation may be interchanged with daily maximum temperature in these calculations. The time of daily observation of dry-bulb temperature, however, may allow for less drying and lower values of KBDI (see Janis 2002 for effect of observation time on daily maximum and minimum temperatures).

Daily precipitation decreases KBDI when 24-h precipitation is greater than 0.51 cm (0.2 inches) or precipitation accumulation over consecutive rainfall days is greater than 0.51 cm. A consecutive rainfall period ends on the first 24-h period with no measurable precipitation. Moisture in upper soil layers has been related to surface litter moisture and surface litter flammability (Hatton *et al.* 1998). As alluded to by Keetch and Byram (1968), precipitation accumulation less than 0.51 cm over 48 h is not considered to ameliorate moisture deficits in the upper soil or surface litter layer and does not go toward reducing KBDI.

KBDI calculations are defined by one of the following equations:

a. $KBDI_t = KBDI_{t-1}$ if $P_t = 0$ cm and $TMAX_t \leq 6.78°C$

b. $KBDI_t = KBDI_{t-1} + DF_t$ if $P_t = 0$ cm and $TMAX_t > 6.78°C$

c. $KBDI_t = KBDI_{t-1} + DF_t$ if $P_t > 0$ cm and $\Sigma P_t \leq 0.51$cm

d. $KBDI_t = KBDI'_t + DF_t$ if $P_t > 0$ cm and $\Sigma P_t > 0.51$cm

$$KBDI'_t = KBDI_{t-1} - 39.37\Sigma P_t. \tag{2}$$

A persistence scenario, whereby KBDI is unchanged, is used when the daily maximum temperature is less than 6.78°C and daily precipitation is zero (equation 2*a*). Equations (2*b*) through (2*d*) allow some degree of drying or increasing fire potential. These equations satisfy the concept of consecutive or continuous water deficiency for drought indices (Byun and Wilhite 1999). When daily precipitation is zero but daily maximum temperature is greater than 6.78°C, KBDI increases proportionally to the daily maximum temperature (equation 2*b*). When daily precipitation is greater than zero but the precipitation over consecutive rainfall days is less than 0.51 cm, KBDI increases proportionally to the daily maximum temperature (equation 2*c*). When daily precipitation is greater than zero and the precipitation over consecutive rainfall days is greater than 0.51 cm, KBDI increases proportionally to the daily maximum temperature but is moderated by the accumulation of precipitation (equation 2*d*). When equation (2*d*) is applied, $KBDI'_t$ replaces $KBDI_{t-1}$ in a solution for DF_t and no threshold is applied to temperature. Precipitation accumulation over consecutive rainfall days, including the current day, is given by ΣP_t and the coefficient 39.37 converts the precipitation term into hundredths of inches. When precipitation accumulation reaches or exceeds 0.51 cm, this amount is subtracted from the precipitation accumulation only on the day of occurrence and only once during a period of consecutive rainfall days.

A time series of KBDI for 2001 is graphed relative to daily maximum temperature and daily precipitation for Columbia, SC, USA (Fig. 1). The seasonal cycle of maximum temperature (smoothed with 7-day running mean) suggests greater potential for drying during the Northern Hemisphere (NH) summer. Daily precipitation events are commensurate with sharp reductions in KBDI. Between precipitation events, however, the rate of KBDI increase is proportional to the daily maximum temperature. For example, modest precipitation after day 250 led to increasing KBDI, albeit at a slower rate than NH summer increases. KBDI in this example is responding to changing daily weather conditions.

Monitoring errors

A program based on Keech and Byram's original paper (1968) was developed to calculate the drought index values for a large number of stations each day. Missing daily maximum temperatures are replaced with persistence estimates of daily maximum temperature. Missing daily precipitation is assumed to be zero. Since zeroing missing precipitation may lead to a dry or increased fire potential bias in KBDI, a series of error logs is automatically generated to indicate missing and estimated daily values. Error logs are reviewed for anomalous values. These values may be adjusted and KBDI recalculated as needed.

Mapping KBDI

Weather networks

Input data for producing high-resolution KBDI maps for the south-eastern United States are derived from near-real-time weather stations contained within SERCC's databases. Data

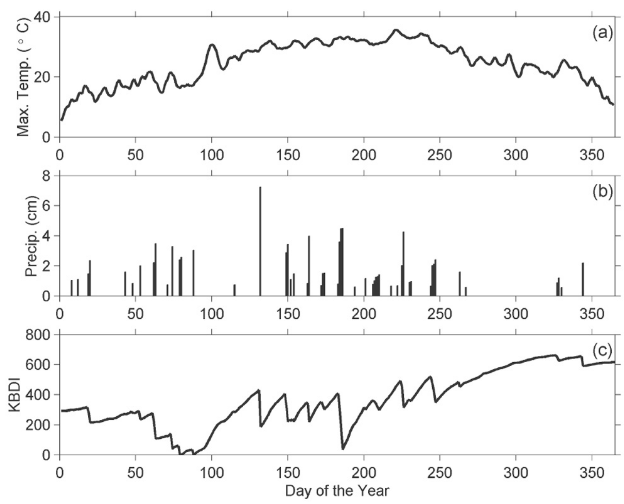

Fig. 1. Time series of (*a*) daily maximum temperature smoothed weekly; (*b*) daily precipitation; and (*c*) daily KBDI for Columbia, South Carolina, USA for 2001.

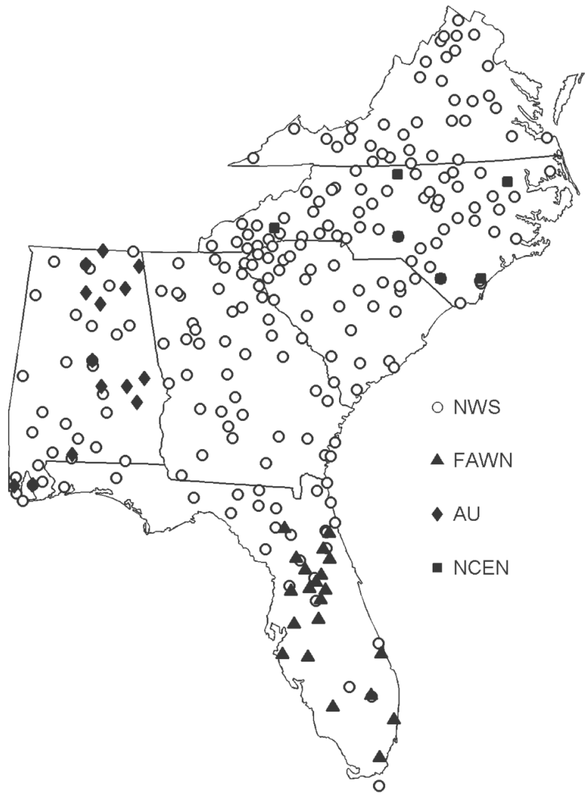

Fig. 2. Distribution of near-real-time weather stations used in daily calculations of Keetch-Byram drought index for the south-eastern United States. Networks include National Weather Services' Cooperative Observer Network (NWS), Auburn University Meso-network (AU), Florida Automated Weather Network (FAWN), and North Carolina Ecological Network (NCEN).

from 261 stations are acquired through satellite systems or automated Internet transfers and are automatically ingested into SERCC's databases at least daily (Fig. 2). Stations are selected based on consistent data reporting and data quality. A majority of stations are derived from the National Weather Services' Cooperative Observer Network while others are derived from various state-operated weather networks. For example,

- Auburn University Meso-network (www.awis.com/mesonet/index.html),
- Florida Automated Weather Network (http://fawn.ifas.ufl.edu/), and
- North Carolina Ecological Network (http://www.nc-climate.ncsu.edu/).

The overall spatial coverage of near-real time weather stations is good. In some areas, state-operated weather networks contribute substantially to enhanced spatial coverage. Yet, areas such as central Florida could benefit from greater spatial sampling. The SERCC continually reviews in-house and external databases to improve the regional density of networks for fire potential and drought monitoring.

Although KBDI generally applies to vegetated areas where fire potential is a function of soil and surface litter moisture, many reliable weather stations in the south-eastern United States are located in urban or built environments. Built environments have different vegetative conditions than surrounding forest and grassland; thus KBDI assumptions regarding field capacity and vegetation may be inaccurate for built environments. Though built environments are not subject to the same fire risks as outlying areas, culling urban weather stations from mapping applications may limit spatial interpolation. Meteorological input parameters from built environments are fairly representative of outlying areas and are likely more representative than distant 'rural' weather stations. Computing KBDI for built environments and interpolating to unknown surrounding locations is perhaps more appropriate than interpolating KBDI over large distances (this assertion has been evaluated for precipitation and temperature: see Willmott *et al.* 1996; Robeson and Janis 1998). It should be noted that the spatial region of interest in the south-eastern United States is regionally homogeneous compared with fire regimes in other parts of the United States and the world.

Mapping techniques

Once a week, the SERCC maps high-resolution daily calculations of KBDI for the south-eastern United States. Developing accurate near-real time KBDI maps depends on reliable point estimates of KBDI at high spatial resolution. Several factors can degrade the accuracy of KBDI maps, both near the point estimates and across large areas. One factor is optimizing the trade-off between high spatial resolution of point estimates and the consistency of KBDI estimates. Since KBDI is a cumulative function, missing input parameters may create inaccuracies over subsequent days. Weather stations with dubious daily reporting records are culled from KBDI mapping regardless of their spatial contribution. Maintaining a dense network of reliable weather stations with adequate spatial distribution throughout the region is imperative for drought and fire potential monitoring.

Determining an interpolation method for estimating KBDI at unsampled locations is another factor for consideration. Spatial techniques for mapping KBDI include, among others, inverse-distance weighting (IDW) and kriging (see Burrough and McDonnell 1998 for discussion of interpolation methods). IDW employs a distance decay function to approximate values at unsampled locations from a neighborhood of sampled locations (i.e. weather stations). The neighborhood for IDW in this application is the full spatial domain. This method reproduces the values at sampled locations. As distance from sampled locations increases, estimates become dissimilar at

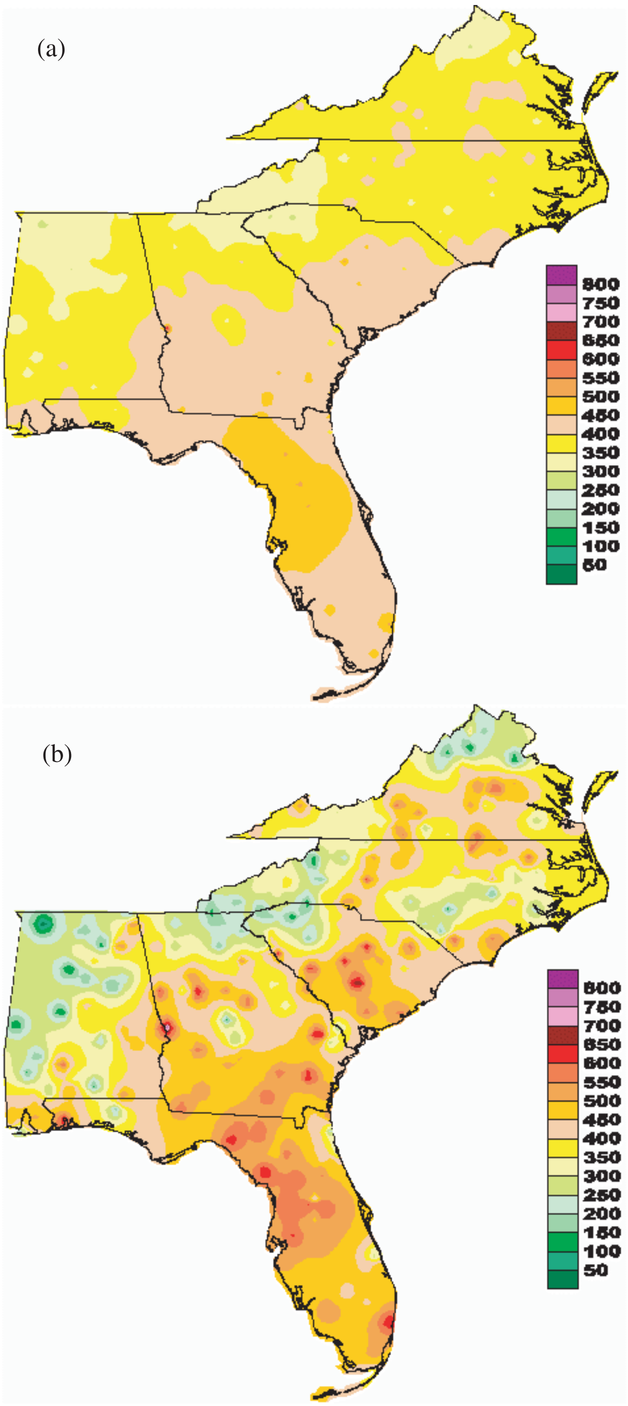

Fig. 3. KBDI mapped using (*a*) IDW-1 and (*b*) IDW-2 for week ending on 9 December 2001.

a rate proportional to the power of the weighting function. IDW is applied to KBDI mapping with weight functions of power one and power two (Fig. 3). This interpolation method with a weighting function of power one (IDW-1) produces very smooth maps of KBDI. This smoothing occurs near sampled locations and provides a flat representation of enhanced or reduced fire potential categories. This interpolation method with a weighting function of power two (IDW-2), however, produces 'spotty' maps with large gradients occurring very near weather stations and little variation between.

Kriging is a geostatistical method that uses the observed spatial variation across the domain as a spatial weighting function. The observed spatial variation, or semivariance, is the average squared difference of station values for all stations separated by predetermined spatial lags. Variogram models fitted to the semivariance typically have three parameters that characterize their shape: sill, range, and nugget (Burrough and McDonnell 1998). Semivariance generally increases from small separation distance to the distance determined by the range. The sill is the plateau in semivariance that occurs at the range. At distance greater than the range, relationships between locations are independent of distance. Within the range, locations that are closer together generally have more similar values. The nugget is the estimated 'non-zero' semivariance at distance zero and accounts for small-scale variations that are unresolved by the sampling network.

Kriging assigns interpolation weights by minimizing the estimation variance between the unsampled locations and the sampled locations. Specifically, the minimization involves solving the fitted variogram model for distances between the unsampled locations and the sampled locations. In this application, a linear variogram model with no sill is used. This variogram model assumes that variation is distance-dependent across the entire domain, but does not dampen or exaggerate the rate of distance decay across any spatial lag. The linear variogram model is relatively generic and may be the most appropriate for operational uses that encompass multiple forms of distance decay. Kriging reproduces exactly the values at sampled locations and uses the observed spatial variance to estimate value in between observations. While IDW relies on a static distance-dependent weight function, kriging makes use of spatial variance patterns over each time step to dynamically construct optimal weights. Kriging creates more visually appealing maps with more realistic spatial gradients between known values (Fig. 4).

To assess the performance of interpolation methods, gridded estimates are compared with KBDI calculations across an independent dataset. Independent data are derived from 124 weather stations in the south-eastern United States that do not report daily precipitation and temperature until the end of each month. For that reason, these data are not included in near-real time mapping of KBDI (i.e. Figs 3 and 4). Daily KBDI is calculated at each of the 124 independent weather stations and related to the nearest gridded estimate on a weekly basis from 14 October 2001 to 22 March 2002 (this time period coincides with the beginning of operational mapping and the most recent independent data at time of

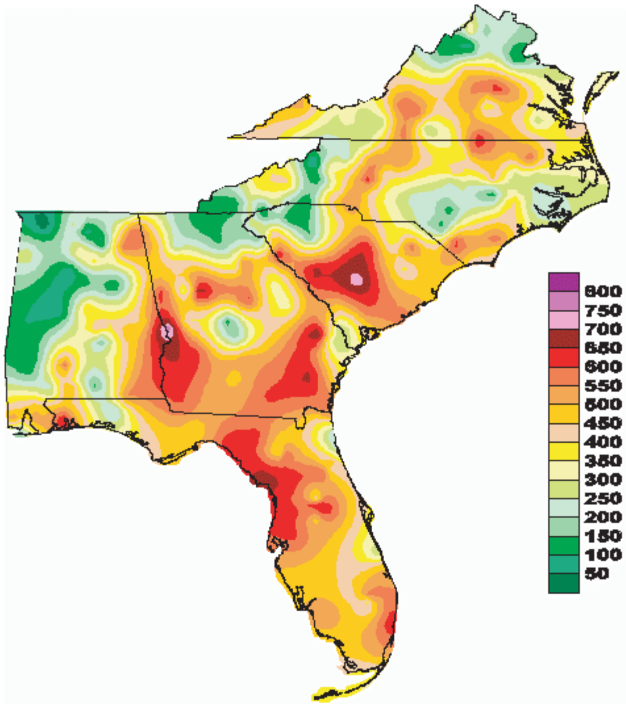

Fig. 4. KBDI mapped using kriging for week ending on 9 December 2001.

Table 2. Summary statistics for three interpolation methods: inverse-distance weighting power-1, power-2, and kriging
Units of KBDI are retained for all statistics except for coefficient of determination (r^2). For independent data, average KBDI is 283 and standard deviation (s.d.) is 197

	IDW-1	IDW-2	Kriging
Average	279	287	295
s.d.	89	122	163
r^2	0.31	0.33	0.25
MAE	140	133	138
RMSE	165	166	183
$RMSE_s$	148	130	117
$RMSE_u$	74	102	141

Table 3. Percentage of land area in the south-eastern United States for KBDI-difference classes mapped in Fig. 6
Differences are computed between gridded estimates of kriging and IDW for the week ending on 9 December 2001. Positive values indicate that kriging produces greater values than IDW

KBDI difference	Land area (%) IDW-1	IDW-2
$250 \leq D$	0.7	0.0
$150 \leq D < 250$	10.8	2.0
$50 \leq D < 150$	30.6	22.2
$-50 < D < 50$	25.8	54.0
$-150 < D \leq -50$	19.6	20.3
$-250 < D \leq -150$	11.3	1.5
$D \leq -250$	1.2	0.0

publication). KBDI from the independent data source is not well estimated by any of the three methods (Fig. 5). IDW-1 has the least scatter, but displays systematic over-estimation of small KBDI and under-estimation of large KBDI.

Components of the root-mean square error (RMSE) quantify the estimation error as random ($RMSE_u$) or systematic ($RMSE_s$). As a benchmark for statistical performance, systematic error should be the lesser of the two components and preferably near zero (Willmott 1981). Though kriging has larger RMSE and comparable mean-absolute error (MAE), it produces KBDI fields that satisfy the properties of lesser $RMSE_s$ (Table 2). Large differences between gridded estimates and independent calculations lead to lower MAE than RMSE for all interpolation types, but especially kriging (see also Fig. 5*c*).

Differences in gridded KBDI between IDW and kriging are mapped (Fig. 6). The methods produce KBDI within ± 50 units of each other over 25.8% of the region for IDW-1 and 54.0% of the region for IDW-2 (Table 3). While there are equal numbers of positive and negative differences between IDW-2 and kriging, IDW-1 is less than kriging across 30.6% of the land area. Large positive and negative differences from kriging estimates are observed over several areas. Moreover, the spatial extent of large differences is typically greater for IDW-1 estimates. In western Alabama large areas of low KBDI (little fire potential) are estimated by kriging but not IDW (kriging estimates are more than 150 units less than

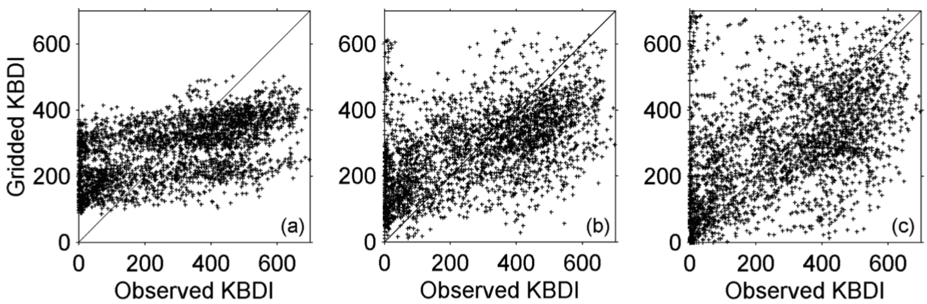

Fig. 5. Scatterplots of KBDI from non-NRT weather stations versus nearest gridded KBDI from (*a*) IDW-1; (*b*) IDW-2; and (*c*) kriging interpolation schemes.

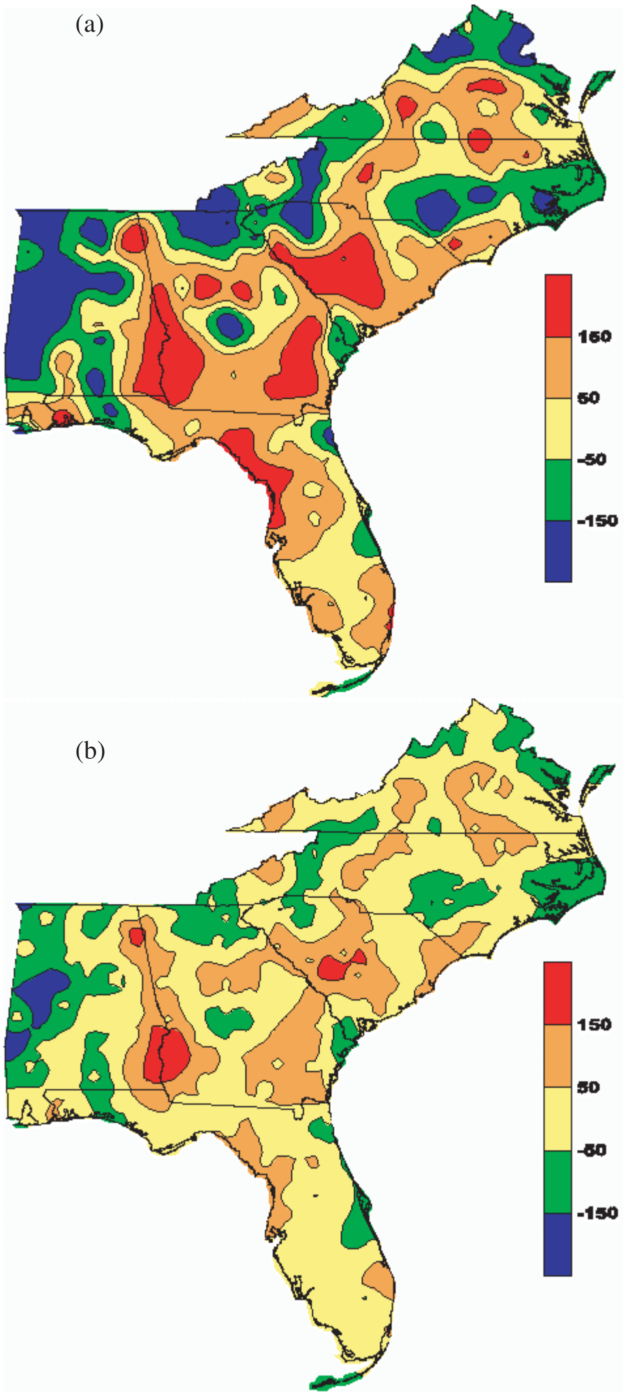

Fig. 6. Difference maps for KBDI interpolation by (*a*) kriging minus IDW-1 and (*b*) kriging minus IDW-2 for week ending on 9 December 2001 (map in Fig. 4 minus maps in Fig. 3). Positive values indicate that kriging produces greater values than IDW.

IDW estimates). Though western Alabama had limited fire potential for this time period, the combined effect of IDW interpolation and limited underlying sample density constrained low KBDI estimates to very near sample locations. Along the Alabama–Georgia border and south-eastern Georgia for IDW-1, kriging estimates are as much as 250 units greater than IDW estimates. The large spatial extent of KBDI differences greater than 150 units indicates likelihood for significant under-estimation of fire potential by IDW. In central South Carolina, a large area of ‘severe drought’ and ‘difficult fire suppression’ is estimated by kriging but not IDW. Unlike the previous cases, the underlying network density in South Carolina is dense enough that both procedures should produce maps of widespread fire potential.

Observed wildfires greater than 1 acre (4047 m^2) over central South Carolina during the week ending 9 December 2001 are mapped relative to differences in KBDI calculated by kriging and IDW–2 methods (Fig. 7). The purpose of this map is to illustrate a scenario where IDW-2 interpolation estimates of KBDI decreased with distance away from the weather stations and under-estimated the fire potential at unsampled locations. While IDW-2 interpolation estimates were consistent with moderate fire potential (i.e. greater than 450 units across the outlined area; Fig. 3*b*), all 18 wildfires in the outlined area corresponded with KBDI differences greater than 50 units. Several of these were located in areas where kriging KBDI estimates are at least 150 units greater than IDW-2 estimates. The difference map also confirms that KBDI estimates from the two interpolation methods are more similar near weather station locations, where KBDI is calculated (see ‘yellow’ areas), and become more dissimilar as distance from the weather stations increases. By using the spatial variability modeled from the sample locations, kriging better reflects fire potential in areas between weather station observations.

Weekly KBDI-change mapping

To provide a measure of increasing moisture deficiency or decreasing fire potential, KBDI change maps over a weekly time step are constructed (Fig. 8). These maps help identify areas that may be undergoing rapid changes in moisture status. For example, most areas in the south-eastern United States experienced increased fire potential between the week ending 2 December 2001 and the week ending 9 December 2001. Over this interval KBDI increased by as much as 100 units across the region. After an evaluation period, change maps may be generated every day and added to the suite of KBDI and drought-related products. In conjunction with KBDI maps (e.g. Fig. 4), change maps provide decision makers with another tool for monitoring near-real-time fire potential.

Discussion and Conclusion

Monitoring unfolding hazardous conditions for drought and fire potential is possible with near-real-time point calculations of KBDI. These calculations, combined with other timely information and weather forecasts, allow land

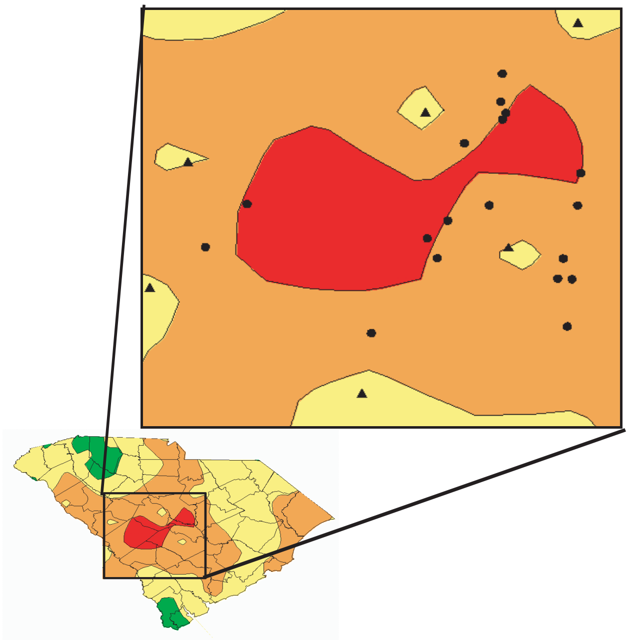

Fig. 7. KBDI difference between kriging and IDW-2 for week ending on 9 December 2001 for South Carolina USA and 25575 km^2 detailed area. KBDI-difference scale is the same as that shown in Fig. 6. Detailed area shows weather station locations (▲) and locations of wildfires greater than 4047 m^2 (1 acre) (●). [Fire information source: South Carolina Forestry Commission.]

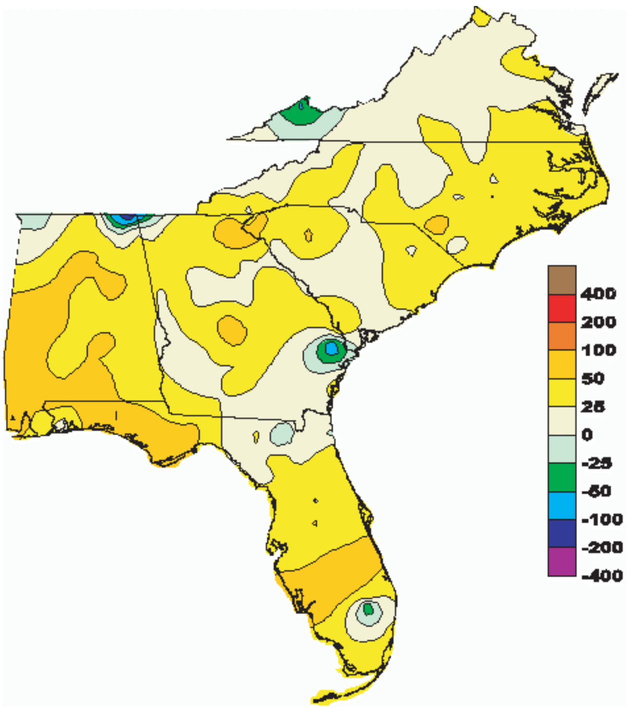

Fig. 8. KBDI change map between week ending on 2 December 2001 and week ending on 9 December 2001.

managers to react promptly to changing weather conditions. Near-real-time (daily or weekly) mapping of KBDI for operational fire potential monitoring is not unique to the SERCC. To varying degrees, national, regional, and state agencies undertake such mapping (e.g. Florida Division of Forestry; http://flame.fl-dof.com/fire_weather/). The National Interagency Fire Center produces daily KBDI maps in support of the Wildland Fire Assessment System (WFAS; USDA 2002). Differences between their KBDI maps and those discussed here are: the number of input weather stations for the south-eastern United States and the choice of interpolation method for spatial mapping.

SERCC calculations of KBDI are based on meteorological parameters from 261 weather stations (operating year-round). Since kriging is based on the observed spatial variability in KBDI it facilitates better interpolations and maps than IDW, especially in areas of diminished network density. WFAS maps for the contiguous United States are constructed with as many as 1500 weather stations (USDA 2002). While a majority of these stations are located in 11 western states, only 103 stations are located in the south-east and many report only during the 'fire' season. WFAS maps are based on KBDI interpolated to a grid using an IDW technique. WFAS KBDI maps, however, provide a national perspective of fire potential and, like all spatial fields, will perform better in regions of high station density.

While it is reasonable for national, regional, and state KBDI mapping to coexist, the methods described here focus on maintaining high-resolution input parameters and improving interpolation techniques for enhanced regional mapping. As a side note to the evaluation of spatial mapping methods, it is apparent that neither kriging nor IDW estimated the KBDI calculated from an independent data set very well (e.g. Table 2; Fig. 5). The moderate errors incurred by interpolating KBDI over space suggest enhanced network density could provide a substantial boost for spatial mapping of KBDI. This is almost certainly more imperative in areas with greater climate and fire regime variability than the south-eastern United States.

Much of the south-eastern United States displays seasonal patterns of average KBDI. During a particular season KBDI may be small in the absolute sense, but large in the relative sense of moisture deficiency and fire potential. Lorimer and Gough (1988) suggested an expression of KBDI as a departure from normal KBDI. A similar approach might be to use mean monthly precipitation along with mean annual precipitation to retain the original KBDI scale but also provide a relative expectation of seasonal moisture variability. Since mean annual precipitation is related to vegetation density and evapotranspiration by empirical coefficients, care should be taken when attempting this or any modification to the original KBDI algorithm. Uncovering and documenting the seasonal probability functions of KBDI across many climatic regimes would also provide useful insight to some fundamental properties of the KBDI.

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