Exurban Change Detection in Fire-Prone Areas with Nighttime Satellite Imagery

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Abstract

Fire-prone landscapes are increasingly being settled. Monitoring this development is an emerging need, and a low-cost method would benefit emergency managers. Existing change-detection methods can be expensive and time consuming when applied to low-density urban change in large, vegetated areas. Nighttime satellite imagery is explored as means for addressing this problem, and a case study is presented for Colorado. The results indicate that from 1992–2000, Grand County had the greatest absolute increase in ambient sprawl into fire-prone areas (215 km^2), but Teller County had the greatest percentage increase (7.3 percent). In 2000, La Plata County had the most ambient development in fire-prone areas (909 km^2), but Jefferson County had the greatest percentage (42 percent). The paper concludes with a discussion of the prospects and problems of the approach.

Introduction

Fire-prone landscapes are increasingly being settled (GAO, 1999). Densely vegetated areas with panoramic views and proximal outdoor recreation offer an appealing alternative to urban and suburban living (McGranahan, 1999). Furthermore, advances in telecommunication technology are allowing people to live further from cities. This is impacting development rates in many fire-prone, exurban areas. In most locales, this growth is gradual, while in others it is very rapid with near year-round construction. New residents typically have little to no knowledge of fire recurrence intervals and are generally not accepting of the notion that they are building a home *between* large fires. Thus, emergency managers must plan for the next large event in the face of a steadily growing at-risk population and housing stock.

Monitoring urban change in hazardous areas is a critical input into the emergency management process (Radke, *et al.*, 2000). It is particularly important in risk assessment, loss estimation, mitigation, and evacuation planning (Cova and Church, 1997; Cova, 1999; Cova and Johnson, 2002). Urban change-detection is an inherently geographic enterprise because development rates vary spatially. Unfortunately, changing settlement patterns are not well-monitored in most fire-prone areas. Simple questions like the amount of development in a defined area for a given time period are costly and inconvenient to answer at scales larger than a city or county. This is important because fire protection and emergency services may be declining relative to population growth in some fire-prone areas, as local and state governments cannot keep pace with the change. For this reason, a simple, low-cost means for monitoring development in fire-prone regions could help agencies allocate emergency resources and coordinate adjacent jurisdictions.

A number of remote-sensing techniques exist for urban change detection that have been applied to core urban areas and the urban-rural fringe (Jensen and Toll, 1982; Gong and Howarth, 1990; Jensen, 1996; Ridd and Liu, 1998; Ward, *et al.*, 2000; Ryzner and Wagner, 2001; Zhang, 2001; Zhang, *et al.*, 2002; Civco, *et al.*, 2002; Herold, *et al.*, 2002). Large vegetated exurban areas complicate the urban change-detection process because it can be expensive and time-consuming to translate spectral signals from roads, rooftops and patios into housing densities, population counts, and ultimately human vulnerability. One approach to this problem is to define the change in terms of emitted light rather than subtle changes in land-cover type. Nighttime satellite imagery provided by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) has been used to map and monitor fires, estimate population densities, delineate urban land cover, identify land-use conflicts, map greenhouse gas emissions, and characterize housing distributions in wildlands (Elvidge, *et al.*, 1997; Imhoff, *et al.*, 1997a; Imhoff, *et al.*, 1997b; Doll, *et al.*, 2000; Sutton, *et al.*, 2001; Elvidge, *et al.*, 2001a; Lo, 2002; Schimdt, *et al.*, 2002). It also holds potential to be a low-cost means for detecting urban change in fire-prone areas.

In this paper, we present a method and case study in using nighttime satellite imagery for urban-change detection in fire-prone areas. The paper begins with background on fire hazard mapping and urban change detection. Data and methodological issues are discussed, and the results of a study are presented for Colorado. We conclude with a discussion of the results and areas for further research.

Background

Fire Hazard Mapping

Fire hazard mapping is of growing interest in many circles, and a variety of contemporary methods exist. Most approaches are based on the trio of fuel, climate, and topography, where the focus is typically better estimations of fuel loads (Keane, *et al.*, 2001; Schmidt, *et al.*, 2002). These methods often incorporate fire-ignition frequency data (Neuenschwander, *et al.*, 2000) and generally require detailed data, such as forest structure, fuel moisture, and canopy closure (Radke, 1995). Because we are interested in developing a general, fine-grained

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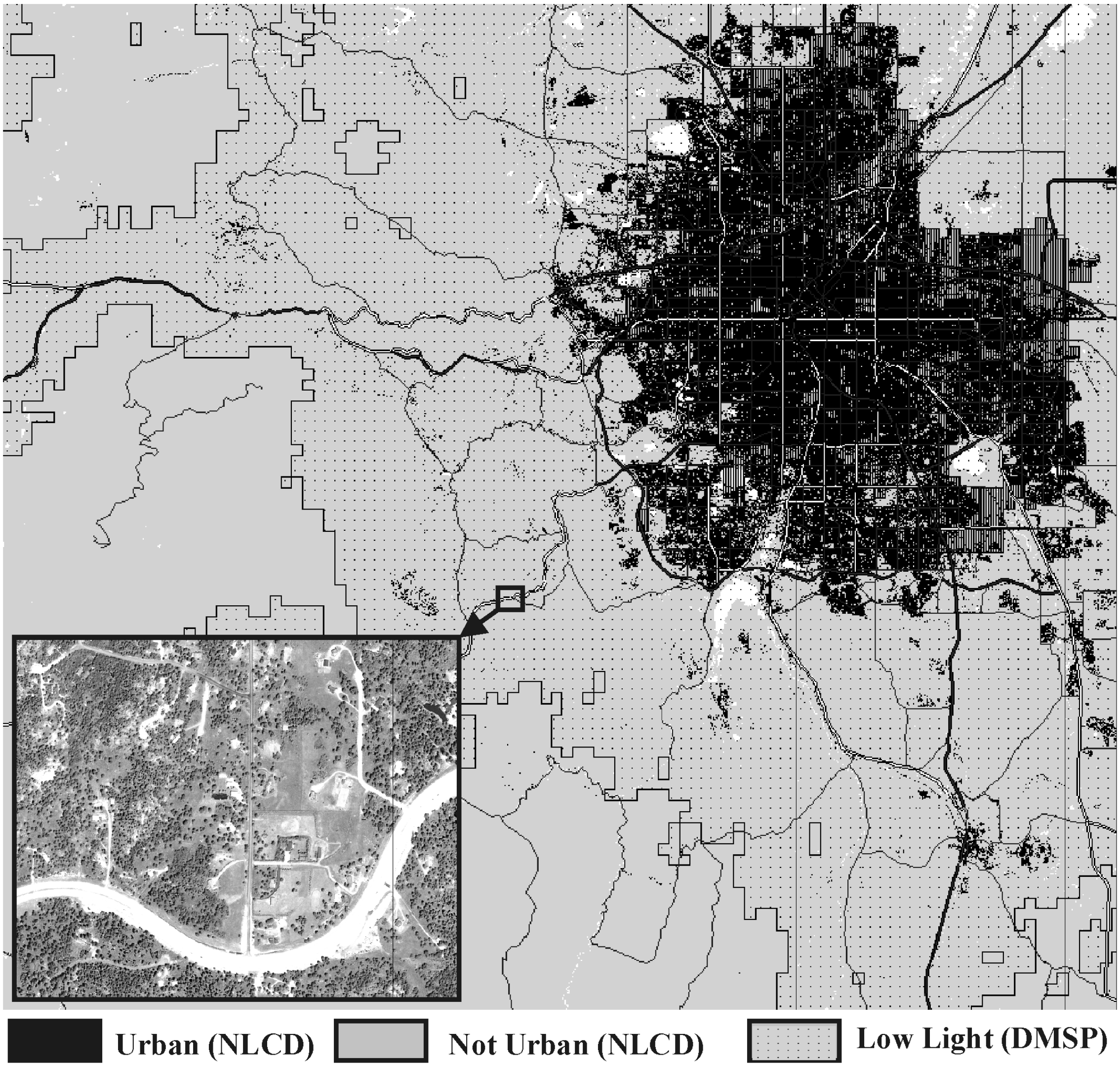

Figure 1. National Land Cover Data (NLCD) with an Ikonos inset and DMSP overlay.

indicator of severe fire risk, our approach is to recognize the importance of forest types in historical fire regimes and the likelihood of extreme fire events. We assume that risk is a combination of fire frequency and the likelihood of an extreme, crown-burning fire that places life and property at risk. This approach recognizes that different forest types have different fire regimes and that climate is often a dominant factor in determining the timing, location, and severity of extreme wildfires (USFS, 2002). Although it is important to examine the efficacy of short-term mitigation measures to reduce severe forest fires (Pollet and Omi, 2002), we also approach the problem from a long-term planning perspective, considering decade to century time scales, and across large extents (states to regions) (Hann and Bunnell, 2001). The approach taken in this research uses widely-available, statewide-extent, fine-grain (30 m) data (e.g., USGS National Land Cover Dataset (NLCD) and Digital Elevation Models (DEM)).

Urban Change Detection in Fire-Prone Areas

As noted, it can be expensive and time-consuming to detect urban change in large, vegetated regions when the land-cover change is subtle. Unlike dense urban areas, residents typically embrace the vegetation in these areas and shun a conversion to impervious land-cover types. For example, Figure 1 depicts an area classified as "evergreen forest" in a 30 m National Land Cover Database (NLCD) derived from Landsat imagery (Vogelmann, *et al.*, 2001). An Ikonos image inset is provided for one NLCD cell to show that there is considerable residential development in this area, as many roads and homes have been built in the forest. Furthermore, to highlight the potential for DMSP-OLS to detect this growth, superimposed on this map is the boundary of an area classified as *low light* from a DMSP-OLS image in 2000 that includes the Ikonos inset. This demonstrates that although the DMSP-OLS data is much coarser than the NLCD map (1 km versus 30 m), it is reasonably suited for detecting urban change in fire-prone areas.

Another data set that is very useful for modeling urban change in hazardous areas is the U.S. census. The census includes population and demographic information that is especially useful in assessing human vulnerability (Cutter, *et al.*, 2000). One drawback with the census is its limited spatial and temporal resolution. In dense urban areas, it may have relatively high spatial detail, but this generally declines in exurban areas where tracts can become very large (Theobald, 2001). In exurban areas, most remote sensing platforms offer a much higher level of spatial detail (Jensen and Cowen, 1999).

Second, the census is performed on a decadal time scale and significant (and interesting) change can occur within and across ten-year windows. There are many satellite platforms that offer much greater temporal resolution. Finally, the census varies in its spatial detail, and there may be statistically appealing reasons for collecting data on regular spatial and temporal intervals. These factors warrant exploring nighttime satellite imagery as a means for monitoring the spatial dynamics of human vulnerability in fire-prone areas.

Data and Methods

DMSP-OLS Data

The acquisition and processing of DMSP-OLS imagery have improved substantially in the last ten years. The transition from analog to digital took place in 1993, and this has made it possible to use the thermal band to screen for clouds and produce multi-temporal mosaics of city lights, gas flares, lantern fishing, and forest fires (Elvidge, *et al.*, 2001b). The sensor was originally designed to see lunar radiation reflected off clouds. This low light sensitivity left many of the earlier image products with saturated sections in the centers of urban areas. This problem was addressed using the production of a *low-gain* product in which the gain of the sensor was turned down on orbits that were within a few days of the new moon. Radiance-calibrated global data products that do not suffer from saturation have been produced from multi-temporal mosaics of the low-gain orbits. Nonetheless, the low-gain products are only available as of 1996.

In this study, we used a Nighttime Lights Change Detection 1992/1993–2000 data set developed by Chris Elvidge at NOAA's National Geophysical Data Center. In order to allow for inter-temporal comparability, we could not use low-gain imagery; consequently, sensor saturation occurs in urban centers. The DMSP-OLS data used were derived from the smoothed nighttime passes of the platform. Only dark portions of the lunar cycles (new moon ±3 days) were used from the months of September, October, and November. The 1992/1993 data were obtained from the F10 platform, and the year 2000 data obtained from the F15 platform. Mid-summer orbits were avoided because of solar contamination (glare), and winter orbits were avoided because of the possibility of overglow caused by snow on the ground. Only the centers of scans were used to improve geo-location accuracy and to reduce the IFOV (Elvidge, 2003). It is important to note that this data set is experimental and has not been peer-reviewed, but it is freely available.

DMSP-OLS data is 6-bit, so DN values range from 0 to 63 (64 unique values). Figure 2 shows a scatter plot of the two DMSP-OLS images. Pixels along the diagonal did not change from time period 1 to 2, while pixels above the diagonal increased in brightness and pixels below the diagonal decreased in brightness. The scatter plot is slightly misleading because there are approximately 34 million pixels in the study area, and most lie on or above the diagonal. However, given the discrete nature of the 6-bit data, it appears that there were many pixels that decreased in brightness. This might be due to the fact that the 1992/1993 data were obtained from a different platform than the 2000 data. Also, land cover change between the image acquisition periods (e.g., leaves) may affect reflectance levels in addition to ephemeral light like large construction sites. For this reason, pixel values in time period 1 may have been greater in some areas than time period 2. Despite these obvious drawbacks for our application, this is the best available data.

To simplify the change detection process, the DMSP-OLS data were classified into three classes: no-light, low-light, and saturated. Pixels with a value of 0 were classified as *no-light*, pixels with a value ranging from 1 to 62 were classified as *low-light*, and pixels with a value of 63 were classified as *saturated*. The three classes were checked against housing density from the 2000 census, population density from the 1990 census, and population density from the LandScan 2000 population density dataset (Dobson, *et al.*, 2000). Table 1 shows how the no-light, low-light, and saturated classes correspond with housing and population density. These differences were tested using an Analysis of Variance and are significant at the .0001 level. This classification scheme leads to a three-by-three change-detection matrix with four relevant types of change (Table 2). Figure 3 shows the spatial pattern of the classification scheme for the two time periods in the study area, but at this scale it is not possible to make a meaningful visual comparison.

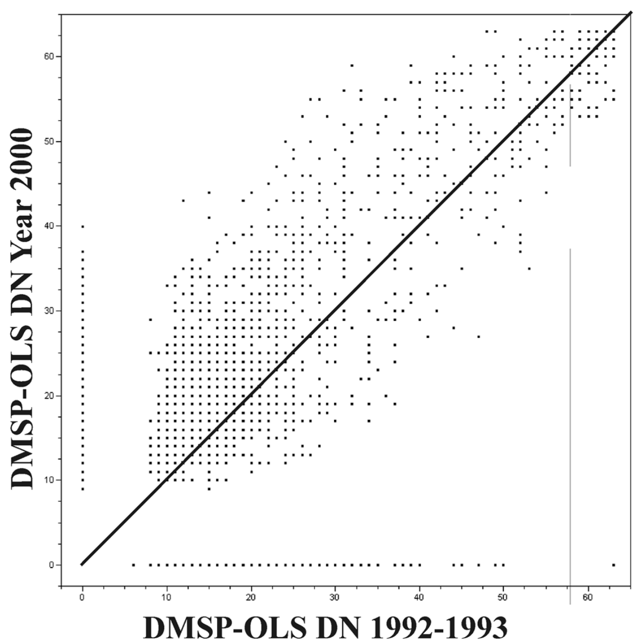

Figure 2. Bivariate scatterplot of DMSP 1992–93 against DMSP 2000.

TABLE 1. A COMPARISON OF DMSP LIGHT LEVELS WITH CENSUS DATA FOR 2000

DMSP OLS (2000) Classification	Housing Density (units/acre) from Census 2000
No Light	0.0017
Low Light	0.132
Saturated	2.437
DMSP OLS (92/93) Classification	**Population Density (persons/km^2) from 1990 Census**
No Light	0.64
Low Light	48.26
Saturated	1286.5
DMSP OLS (2000) Classification	**Population Density (persons/km^2) from LandScan 2000**
No Light	0.5053
Low Light	55.5
Saturated	983.5771

Table 2. A Change Detection Matrix with the Four Relevant Types of Change

Time 1 (1992–93)	Time 2 (2000) No Light	Low Light	Saturated
No Light	0	1	0
Low Light	2	0	3
Saturated	0	4	0

Extreme Fire-Risk Mapping

Our fire-risk mapping method relies on distinguishing seven forest types commonly found in the Rocky Mountain West (Table 3). Two components of these forest types were used: fire frequency and fire severity. Fire frequency was modeled as the annual probability of fire, based on the inverse of the average historical fire frequency. To compute a map of frequency, we reclassified a modified National Land Cover Dataset map that provided species-level information (Theobald and Romme, 2002) using the annual frequency of fire. The frequency values were normalized to range from 1 to 10. For fire severity, we incorporated a fine-scale moisture index that is based on a DEM and differentiates wet riparian areas, moist north-facing mid-slopes, dry south-facing slopes, and very dry ridge-top conditions (Theobald and Romme, 2002). The severity score was adjusted to range from 1 to 10, based on fire behavior of each forest type (Table 4). Finally, we multiplied the frequency and severity scores and averaged the values with a one-quarter mile filter. Note that we were not able to map different fire severities in ponderosa pine forests as a function of canopy closure and stand density because a statewide map of canopy cover is not currently available (although NLCD 2000 intends to map this at 30 m resolution). The final extreme fire risk map is shown in Figure 4 where darker areas have a greater risk of an extreme fire.

Results

The two DMSP-OLS images for 1992–93 (time 1) and 2000 (time 2) were coregistered with the extreme fire risk map (nominal 1 km resolution; 4448 rows and 7656 columns) for the state of Colorado. Figure 5 depicts the spatial extent and pattern of the change across the two time periods, where lighter areas increased in emitted light and darker areas decreased in emitted light. No pixels transitioned from no-light to saturated, and none went from saturated to no-light, so these cases are not depicted. The diagonal in Table 1 (no-change) is represented with a neutral gray. Figure 5 shows that there are many cases where a pixel emitted less light from time period 1 to 2, but they tend to be clustered. The most prominent feature is the increase in light (no-light to low-light or low-light to saturated) on the fringe of many urban and exurban areas. These newly lighted areas often extend into forested, fire-prone areas. Overall, Figure 5 answers the question of where ambient development occurred in Colorado from 1992–93 to 2000 from a DMSP-OLS perspective.

To examine where ambient sprawl exists in fire-prone areas in 2000, Figure 6 shows the extent of 'low-light' within areas of non-zero fire risk (i.e., 1–40 in Figure 4). Areas

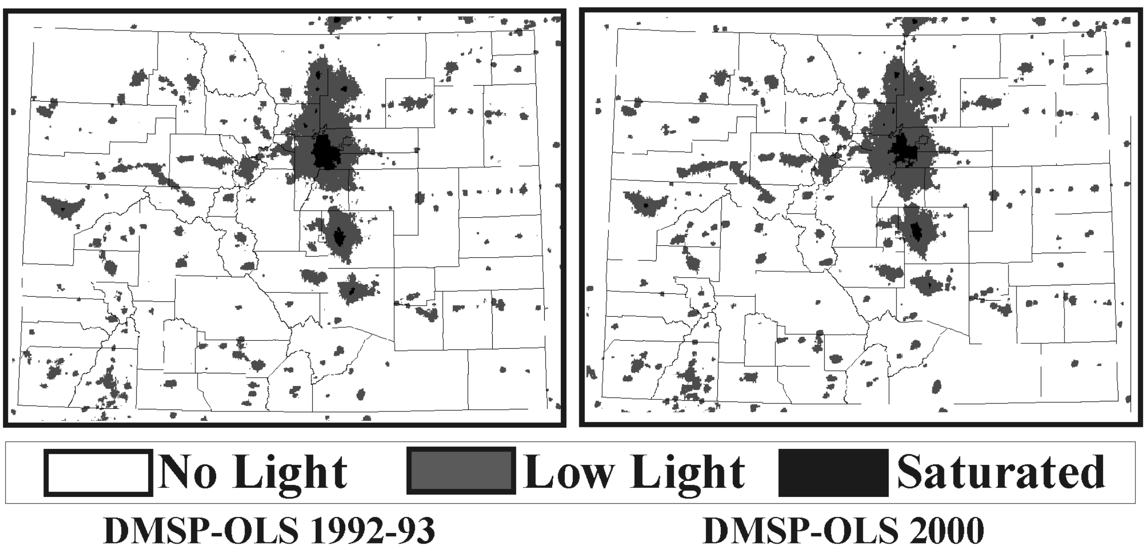

Figure 3. Classifying DMSP data into three categories for two time periods.

Table 3. Seven Forest Types found in Colorado and their Average Historical Fire Return Interval (Romme and Knight, 1982; Veblen, *et al.*, 2000)

Forest Type (dominant species)	Average Return Interval (years)	Annual Prob. of Occur	Typical Fire Severity
Lower montane (Ponderosa pine)	20	0.05	Low (if low density) High (if high density)
Montane (Ponderosa pine)	50	0.02	Mixed
Mixed Conifer (Lodgepole pine, Douglas fir)	100	0.01	High
Upper montane (Engleman spruce, sub-alpine fir)	300	0.003	High
Aspen	150	0.007	Low
Pinyon-Juniper	300	0.003	High
Shrubland	75	0.013	High

Table 4. Fire Severity Scoring Method for the Seven Colorado Forest Types

Forest Type (dominant species)	Severity Score (1–10)			
	Riparian	Moist	Moderate	Dry
Lower montane (Ponderosa pine)	1	2	3	4
Montane (Ponderosa pine)	1	2	3	4
Mixed Conifer (Lodgepole pine, Douglas fir)	7	8	9	10
Upper montane (Engleman spruce, sub-alpine fir)	7	8	9	10
Aspen	1	2	3	4
Pinyon-Juniper	6	7	8	9
Shrubland	6	7	8	9

emitting light but without extreme fire risk are not shown. This figure shows that there is a significant amount of ambient sprawl in fire-prone areas in Colorado. Also, the greatest exurban fire risk is in the mountains just west of Denver and Colorado Springs with the second greatest risk area along I-70 from Denver to Glenwood Springs, Highway 82 from I-70 to Aspen, and around Durango. Figure 6 answers the question of where the greatest extreme-fire vulnerability lies in Colorado.

Attribute data were analyzed to compare county fire risk levels and dynamics. Table 5 shows the top 20 counties in Colorado sorted by their total low-light pixels in fire-prone areas. For each county, the table lists the county area (km^2), and the change in the respective categories of no-to-low-light, low-to-no-light, and the net change between the two. Following this are columns for no-to-low and low-to-no light and the net change for areas at fire risk (i.e., extreme fire risk is non zero in risk map). The last three columns represent the total low-light areas in the county in 2000, the percent of the county at fire risk, and the percent change in fire risk from 1992/1993 to 2000. Although Grand County had the greatest absolute change in low-light area in fire-prone areas (215 km^2), La Plata County had the most low-light in fire-prone areas in 2000 (909 km^2), Jefferson County had the greatest percentage of low-light in fire-prone areas (42 percent), and Teller has the greatest percentage increase in low-light in fire-prone areas from 1992/ 1993 to 2000 (7.3 percent). Table 5 could be used to compare the change in exurban development in fire-prone areas in various counties with the commensurate increase or decrease in funding for fire fighting and emergency services in a more comprehensive economic study.

Figure 7 is a close up of the four counties with the greatest increase in low-light area in areas of non-zero fire risk from 1992/1993 to 2000. La Plata County is an interesting case because it does not have zoning laws, so it follows that this county might surface in an analysis of exurban sprawl in fire-prone areas. Garfield County is also interesting because it includes Glenwood Springs where there were large fires in the summer of 2002. In general, it is fortunate (and surprising) that such large fires could occur in high risk counties without significant residential loss. This figure demonstrates the potential for DMSP-OLS data to describe the pattern of development in fire prone areas in addition to calculating aggregate statistics.

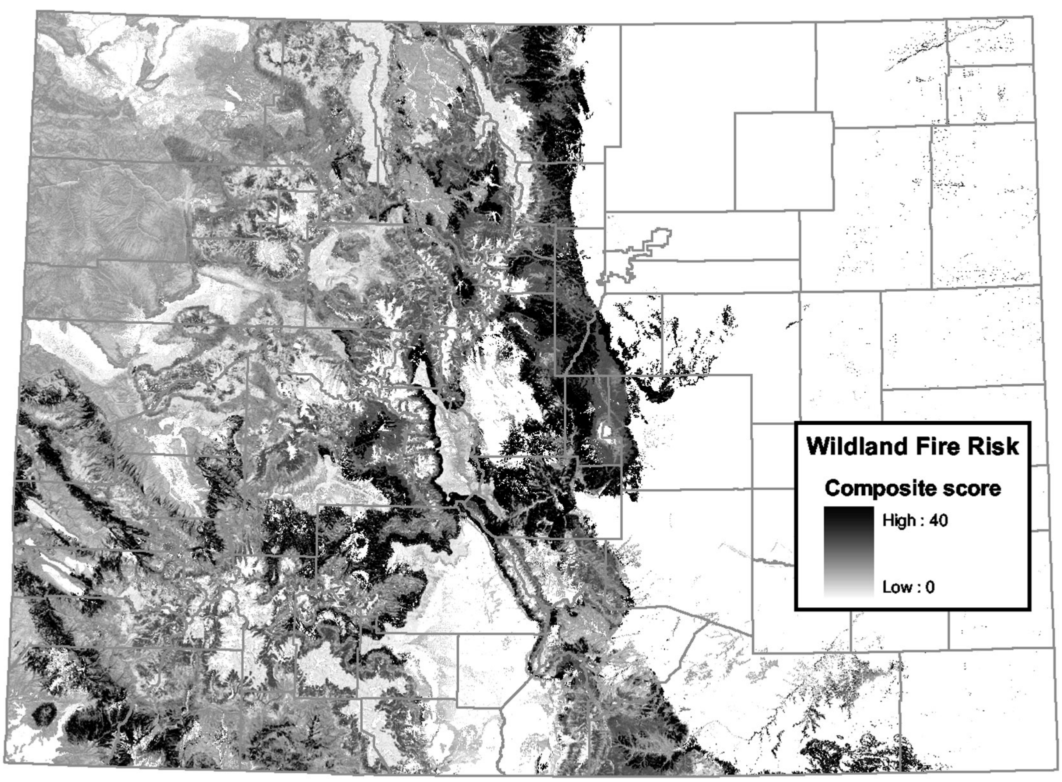

Figure 4. An extreme-fire risk map for Colorado.

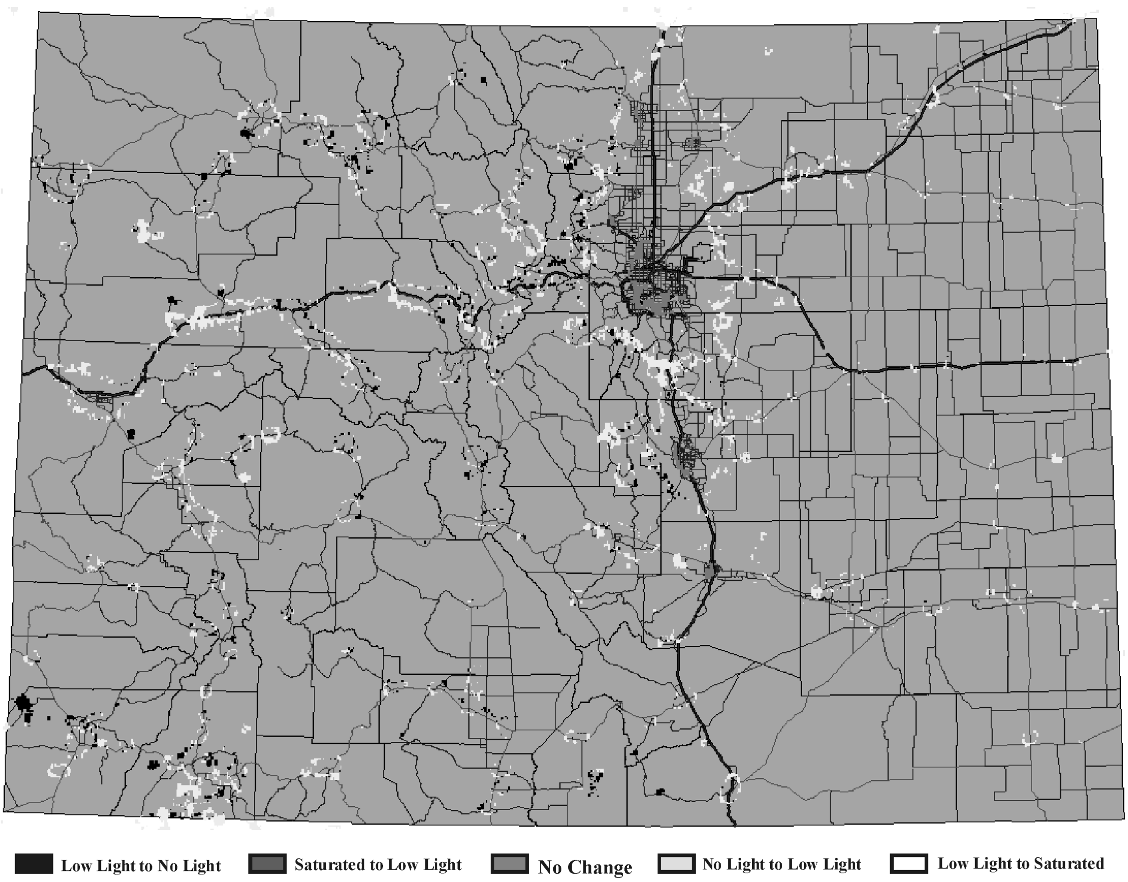

Figure 5. Areas of change in the DMSP imagery from 1992–93 to 2000.

TABLE 5. AGGREGATE COUNTY-LEVEL RESULTS FOR THE CHANGE-DETECTION METHOD

County	Area km^2	No-to-Low km^2	Low-to-No km^2	Net Change km^2	No-to-Low Fire Risk km^2	Low-to-No Fire Risk km^2	Net Fire Risk km^2	Low 2000 Fire Risk km^2	%County Fire Risk 2000	%Change Fire Risk 1992–00
Grand	4837	261	37	224	250	35	215	643	13.3	4.5
Garfield	7776	335	77	257	280	72	208	783	10.1	2.7
La Plata	4397	359	154	206	336	148	188	909	20.7	4.3
Eagle	4446	166	37	130	163	37	126	680	15.3	2.8
Teller	1463	150	41	110	146	39	107	371	25.3	7.3
Douglas	2251	266	30	236	121	16	105	336	14.9	4.7
Mesa	8657	185	51	134	126	39	87	675	7.8	1.0
Summit	1619	130	35	95	112	31	81	592	36.6	5.0
Rio Blanco	8375	139	62	77	137	62	75	442	5.3	0.9
Archuleta	3505	70	3	67	69	3	66	188	5.4	1.9
Delta	3084	123	52	70	97	33	63	246	8.0	2.1
Montrose	5809	100	26	74	72	12	59	212	3.6	1.0
Park	5811	75	20	55	72	18	54	213	3.7	0.9
Fremont	3978	96	30	66	69	19	50	162	4.1	1.3
Jefferson	2013	77	28	49	77	28	49	848	42.1	2.4
Pitkin	2519	63	24	39	63	24	39	302	12.0	1.5
Gunnison	8517	78	47	31	76	41	35	293	3.4	0.4

Discussion

The principle advantage of using light as a measure of exurban change in fire-prone areas is that it is relatively inexpensive and requires much less effort than existing urban change detection methods. The spatial and temporal resolution of DMSP-OLS data is fine enough that it might improve upon the census as means for monitoring this change. Furthermore, the data is available world wide and includes areas that may not be in the census like national park campgrounds, cabins on federal land, and other excluded areas of human occupancy. Finally, it provides a consistent framework to analyze risk across political boundaries (i.e., counties and states), and it is free.

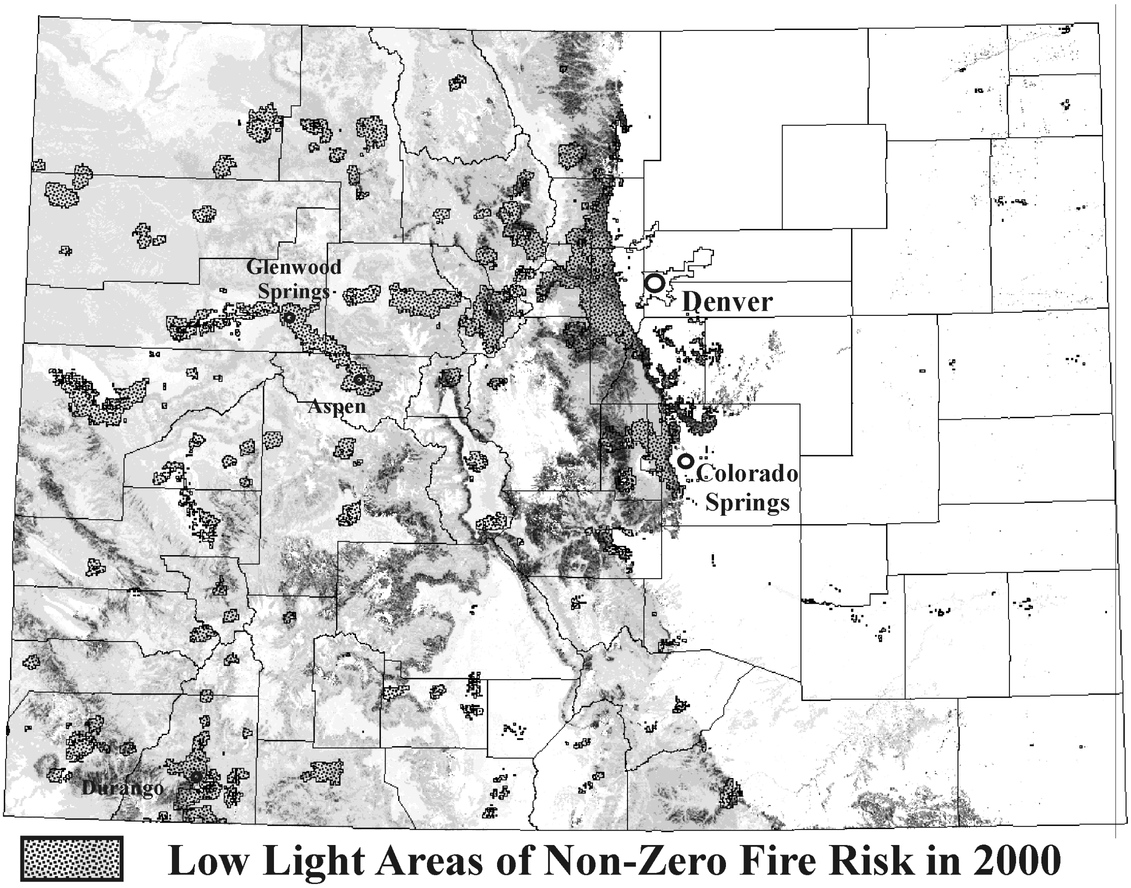

Figure 6. Areas of Colorado with non-zero fire risk and low-light levels.

The principle weakness of using DMSP-OLS data for change detection in fire-prone areas is the 1 km resolution, which limits its use for fine-grained analysis. There are also spectral limitations, and the low-gain images may not be sensitive enough to pick up all human-related change such as campgrounds and cabins. The snow and leaf seasonal factors also make the data imperfect for change detection, but this may decrease with time as the collection and processing procedures for DMSP-OLS data become standardized.

Future research questions might center on reducing the effects of snow and other seasonal variations. The question of classification scheme is also an issue; this research relied on a no-light, low-light, and saturated classification scheme, but there are refinements that could be made. In other words, what is the best level of information granularity (classification detail) to monitor urban settlement in fire-prone areas? DMSP-OLS data may also have application in predicting future change in these areas in an urban growth modeling context.

Conclusions

Rapid growth in exurban, fire-prone wildlands is precipitating the need for new tools to monitor this change. This paper explored the use of nighttime satellite imagery in monitoring exurban change in Colorado's most fire-prone areas. DMSP-OLS data was combined with a map of extreme wildfire risk that relied on widely available data to analyze the change. The results indicate that DMSP data is not without problems, but that the method is relatively inexpensive. Many of the problems of working with this data may be eliminated as data acquisition and processing methods improve and become standardized.

There are many directions that might be pursued following this initial study. One of the greatest needs is for more research into the quality of the results of using DMSP data to detect exurban change in relatively vegetated areas. Although the initial results provided in this paper are promising, we were not able to make strong accuracy statements regarding the absolute change in ambient sprawl as it relates to housing, infrastructure, and population densities. This could be accomplished though more studies at the county scale where this data is easier to acquire and field check. Furthermore, using a low-gain DMSP image, preferably from the same platform, for both time periods would allow for a much finer classification scheme than no-light, low-light, and saturated. Finally, there is much to be gained in applying the method presented in this paper in varied locales because changes in emitted light can be related to a variety of activities on the Earth's surface.

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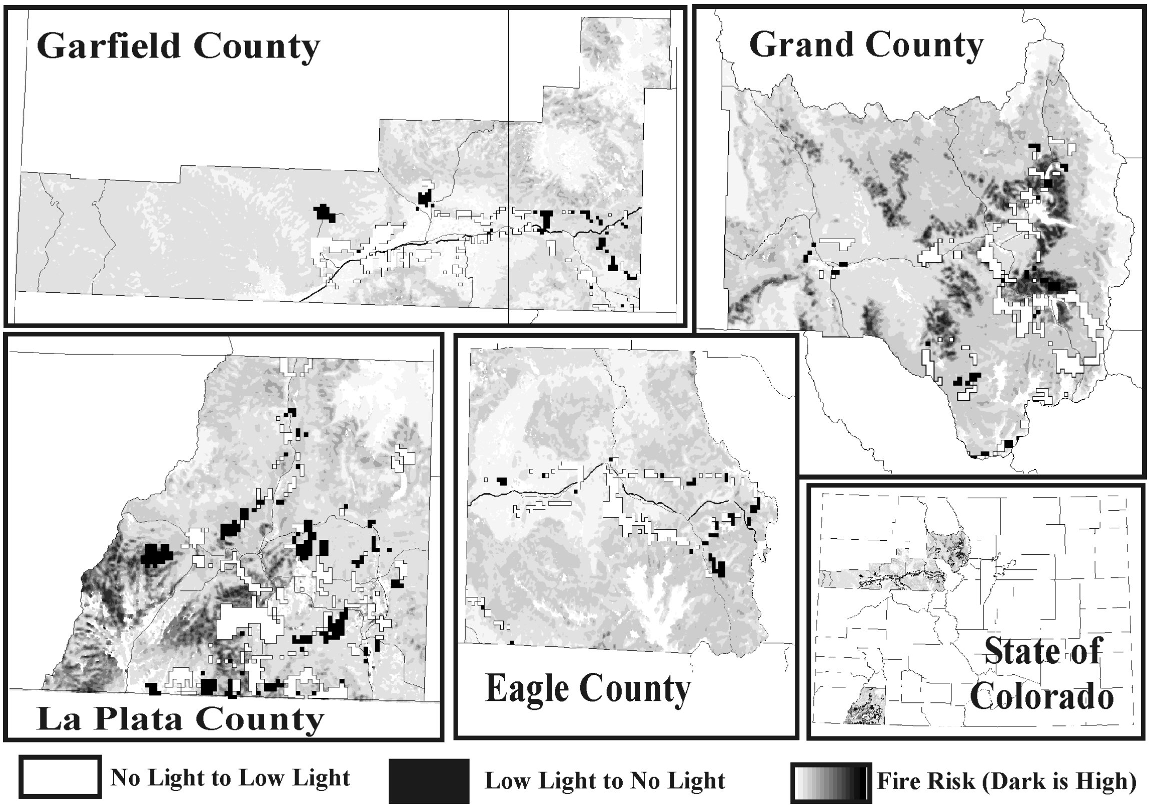

Figure 7. Four Colorado counties with the greatest ambient change (km^2) at-risk to fire.

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