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Monitoring the Land Cover Change in the Historic Range of *Cambarus veteranus* in West Virginia Using a 1973-2013 Landsat Time Series

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MONITORING LAND COVER CHANGE IN THE HISTORIC RANGE OF *CAMBARUS*
VETERANUS IN WEST VIRGINIA USING A 1973-2013 LANDSAT TIME SERIES

A thesis submitted to
the Graduate College of
Marshall University
In Partial Fulfillment of
the requirements for the degree of
Masters of Science
in
Biological Sciences
by
Emma Martha Arneson
Approved by
Dr. Anne Axel, Major Advisor
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ABSTRACT

The crayfish *Cambarus veteranus* is near extinction in its historic range of the Upper Guyandotte River watershed. The biggest threats to *C. veteranus* are mining and road construction. Mining has been a continuous activity in the southern coalfields where the crayfish has historically been found, yet little is known about how much land cover change the practice has done to the region. Crayfish act as important organisms within aquatic ecosystems and without them, those systems are often degraded. Quantifying the change in land cover is important to understanding threats to *C. veteranus* for future protection of the crayfish and its habitat. Using twelve Landsat satellite images from 1973-2013, I performed a supervised land cover classification to track land cover change within the Upper Guyandotte River watershed. There was an overall 5.5% change in land cover with a significant decreasing trend in forested area over time. In addition to overall land cover changing, three, out of seven, subwatersheds where *C. veteranus* was historically found saw significant decreasing trends in forested area as well. The last known location of *C. veteranus* is within one of those three watersheds. This increased disturbance from mining likely explains the near extinction of *Cambarus veteranus*. Without further protection and monitoring the land cover, the crayfish is likely to go extinct within its native West Virginia range.

CHAPTER 1

INTRODUCTION

Mining and the Environment

Coal is historically West Virginia's largest industry. Coal was first discovered in West Virginia in 1742, but extensive mining did not occur until the mid-1800s; mining reached a peak in 1947, producing over 173 million tons of coal that year (WVGES 2004). Mining still provides more than \$6 billion to the state's economy, generates thousands of jobs, and produces over 120 million tons of coal annually (West Virginia Coal Association 2012). The majority of West Virginia's coal mining currently is underground mining, but surface mining makes up more than 40% of the mining practices and techniques in the state (WV Coal Association 2012). Surface mining can fall into three categories: contour mining, area mining, and mountaintop removal mining (Lindberg et al. 2011, WV Coal Association 2012). Mountaintop mining involves clearing forests, stripping the topsoil and using explosives to break up rocks to get to a coal seam. The excess rock and topsoil, or overburden, is pushed into adjacent valleys, creating valley fills (Hartman et al. 2005, Palmer et al. 2010, Lindberg et al. 2011).

Mountaintop mining causes large impacts on nearby streams and biota as well as streams miles away from the active mine. Valley fills bury headwater streams, causing changes in flow patterns as well as changes to water chemistry and biota (Hartman et al. 2005, Bernhardt and Palmer 2011, U.S. EPA 2011). Waters downstream of surface mines also have decreased pH, higher conductivity, higher concentrations of chemical ions such as K^+ , Na^+ , and Cl^- , and sulfate (SO_4^{2-}), as well as increased levels of toxic metals such as cadmium (Cd), zinc (Zn), and selenium (Se), and impaired macroinvertebrate communities (Pond et al. 2008, Palmer et al. 2010, Petty et al. 2010, U.S. EPA 2011 Lindberg et al. 2011, Bernhardt et al. 2012).

Underground mining and surface mining can also produce acid mine drainage (AMD) which is created from the reaction of water combining with oxygen and pyrite to form iron oxide and sulfuric acid (U.S. EPA 2011, Bott et al. 2012). Long-term treatment of streams is required where acid mine drainage has occurred due to acid water draining out of abandoned underground mines or streams being directly exposed to coal material from mountaintop mining. Acid mine drainage pollutes nearby streams and impacts waterways for miles downstream (Lindberg et al. 2011, Bott et al. 2012). The results of mining are numerous and often extremely damaging to the environment.

Monitoring Land Use Changes Due to Surface Mining

Coal mining is the leading cause of land use change in the central Appalachian Mountain region of the United States (Townsend et al. 2009, Bernhardt and Palmer 2011). Monitoring land use changes is important for resource management and assessing environmental impacts. One way to quantify land use and land cover (LULC) change, such as changes in vegetation through time, is through analysis of remotely sensed satellite images. Satellite remote sensing offers a way to monitor large areas of land at frequent time intervals, often at a low cost. The USGS Landsat program has collected satellite images since 1972 at a temporal resolution of 16-18 days.

Using remote sensing to monitor land use changes enacted by coal mining has had some moderate success. Most studies find that mining, both surface and open pit mining, creates disturbance in vegetation over time and poses significant threats to the surrounding environment (Prakash and Gupta 1998, Lu et al. 2007, Latifovic et al. 2005, Charou et al. 2010, Townsend et al. 2009, Tian et al. 2013). Land cover maps classified based on spectral signatures are used to monitor changes in the landscape, often looking at changes in vegetation due to clear-cutting, mining, and urbanization (Cohen et al. 2002, De Fries et al. 1998, Healey et al. 2005, Masek et

al. 2008, Sader et al. 2003, Singh et al. 1997). Different land cover types can be separated based on their spectral signatures, such as deciduous vs. evergreen forest, disturbed vs. non-disturbed areas, and changes in urbanized areas (Peijun et al. 2010, Sader et al. 2003, Townsend et al. 2009). Surface mines are easily identifiable due to their distinct shapes on the landscape but they can be spectrally similar to other land cover types; active mines can be confused with urbanized areas or reclaimed mines with grassland or pasture (Latifovic et al. 2005, Townsend et al. 2009).

Few remote sensing studies have been performed on the southwestern part of West Virginia, also known as the Southern Coalfields. The majority of mining activity in the state occurs in the southern coalfields region (West Virginia Coal Association 2012), yet little is known about the amount of change that has occurred due to mining. The first goal of this study is to use supervised classification of Landsat satellite images to map the changes that have occurred in a section of the Southern Coalfields over a forty-year period.

Crayfish

Crayfish, also commonly called crawdads or mudbugs, are one of the largest and most important benthic macroinvertebrates in freshwater aquatic systems (Taylor et al. 2007). Crayfish act as key species in many food webs. They can act as prey for animals such as raccoons, fish, and hellbenders (Peterson et al. 1989, Hill and Lodge 1999). Crayfish also function as omnivores and detritivores, feeding on macrophytes, periphyton, algae, and other macroinvertebrates (Chambers et al. 1990, Creed Jr. 1994, Charlebois and Lamberti 1996, Vollmer and Gall 2014). Crayfish can have drastic impacts on community structure and function (Lodge et al. 1994, Wilson et al. 2004, Brown and Lawson 2010). Without crayfish, many aquatic systems would not function properly.

There are over 640 species of crayfish in the world, and the Southern Appalachian Mountains of the southeastern United States represents one of the two centers of crayfish diversity worldwide (Crandall and Buhay 2008). Within West Virginia, there are roughly 30 species of crayfish (Loughman 2015). The greatest threats West Virginia crayfish face are anthropogenic, such as mountaintop removal, roadway construction, and the introduction of invasive species like *Orconectes rusticus* and *Orconectes virilis* (Loughman et al. 2009, Loughman and Welsh 2010, Swecker 2012). One of the most imperiled crayfish in the state, *Cambarus veteranus* (the Guyandotte River Crayfish), is currently receiving federal attention. The U.S. Fish and Wildlife Service recently proposed to list *Cambarus veteranus*, along with *Cambarus callainus* (the Big Sandy crayfish) as an endangered species (U.S. Fish and Wildlife Service 2015).

Cambarus veteranus was historically found in the Guyandotte River system and Bluestone River system in Logan, Mercer, and Wyoming counties in streams 10-20 m in width with fast flowing pools (Jezerinac et al. 1995). It can also be found in parts of eastern Kentucky and southwestern Virginia (Loughman 2014, Jezerinac et al. 1995). The last statewide crayfish survey was performed in the summers of 1988 and 1989, where only forty-nine individuals were captured from three watersheds of the seven watersheds it had previously been known to occur. Jezerinac et al. (1995) noted that streams that were suitable for the crayfish were not occupied because of pollution from coal dust and organic matter. There has been little effort to document and monitor crayfish populations in West Virginia since Jezerinac's survey. In 2001, *Cambarus veteranus* was thought to be extirpated from its historic range (Jones et al. 2010) until it was discovered again in 2009 in the Guyandotte River basin by Loughman and Welsh while completing a new statewide crayfish survey (Loughman 2014). A second population of *C.*

veteranus was discovered in the Tug Fork and Dry Fork of the Big Sandy River basin (Foltz 2013, Loughman 2014). Upon the results of genetic testing it was determined that the population in the Tug Fork was a new species, *Cambarus callainus*, separate from *Cambarus veteranus* (Thoma et al. 2014). Within West Virginia, *C. veteranus* can now only be found at one historic site: Pinnacle Creek in the Upper Guyandotte River watershed (Loughman 2014).

Due to the endangerment of *C. veteranus*, it is extremely important to better understand the cause of its decline. By mapping the land cover changes over a long period of time within the watershed where the crayfish is found, I plan to compare mining-related land cover changes to the declining range of crayfish in the region. Using satellite imagery, large land cover changes can be tracked and monitored. If large changes occur near the historic sites of *C. veteranus* I can map those changes over time and show that those changes caused the crayfish to no longer be present at certain sites within the watershed. Mapping land cover change may provide insight into crayfish decline in West Virginia and help identify actions that may be taken to avert the extinction of *C. veteranus* from its native West Virginia range.

METHODS

Study Area

The study area is located in the Upper Guyandotte River watershed in the southwestern part of West Virginia. The watershed is over 673 km² and drains around 2432 km² from parts of Raleigh, Logan, and Mingo Counties and all of Wyoming County; the area is mostly forested and coal mining is the largest industry in the watershed (Downing et al. 2013, Upper Guyandotte Watershed Association 2006). *Cambarus veteranus* has historically been found in the Guyandotte River system and Bluestone River system in Logan, Mercer, and Wyoming counties (Jezerinac et al. 1995) (Figure 1). Loughman (2014) found that while the specimens held by the

United States National Museum (USNM) are *C. veteranus*, they most likely came from Crane Creek in the Big Sandy River Basin and not the Bluestone system as no other specimens of *C. veteranus* have been found in that system since its recording in 1900. For the purpose of this study, I focused on the Upper Guyandotte River watershed exclusively.

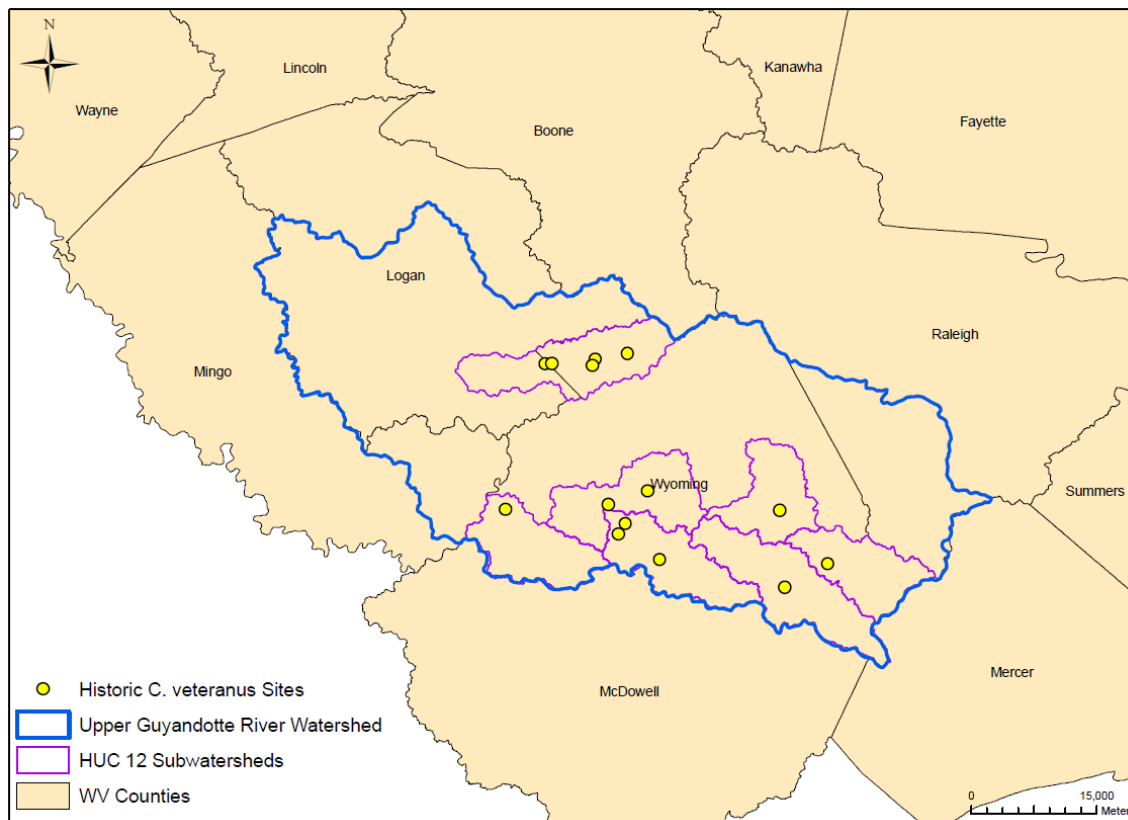


Figure 1. Map depicting *Cambarus veteranus* capture locations within the Upper Guyandotte River watershed and HUC 12 subwatersheds.

Image Acquisition

I used USGS Landsat satellite images for this study. I chose Landsat imagery because it is free and has images collected every 16-18 days dating back to 1972. I was able to obtain images from 1973 to 2013, a forty year time series, to use for this study. Another advantage to using Landsat imagery is that Landsat is always trying to improve upon their dataset and has produced a new product, the Climate Data Records (CDR). The CDR eliminates much of the pre-processing, like correcting for radiance and reflectance, researchers normally must do before

using the images for analysis. The CDR images come pre-processed to surface reflectance and top-of-atmosphere (TOA) reflectance for Landsat 4-5 TM and beyond (there is no CDR for Landsat MSS images). I used TOA-CDR images whenever possible in this study.

Images were chosen based on cloud cover, season, and frequency. Townsend et al. (2009) suggested that smaller time intervals (<10 years) would be better to observe land use changes due to mining, so images were picked on an interval of 3-5 years. This selection process led to three Landsat MSS images, seven Landsat 4-5 TM TOA-CDR images, one Landsat 7 ETM+ image, and one Landsat 8 OLI TOA-CDR image. I could not use a Landsat 7 ETM+ CDR image due to imperfections in the image. Table 1 summarizes the satellite and image information used in this study.

Table 1. List of satellites and dates used in the study.

Satellite	Acquisition Date	Path/Row
Landsat 1-5 MSS	9/3/1973 9/23/1976 9/24/1981	19/34
Landsat 4-5 TM	9/17/1984 9/26/1987 9/21/1991 8/31/1995 9/24/1998	18/34
Landsat 7 ETM+	9/8/2001	
Landsat 4-5 TM	9/11/2005 9/3/2008	
Landsat 8 OLI	9/17/2013	

Image Pre-Processing

Using Erdas-Imagine (v. 14), all images were clipped to the Guyandotte River watershed boundary, using the shapefile of the HUC8 watershed boundaries provided by Natural Resources Conservation Service. All images were then radiometrically corrected as follows. Because I did not have Landsat CDR images for Landsat MSS or ETM+, I had to correct for radiance and

reflection. The Landsat MSS images and the Landsat 7 ETM+ image were corrected by converting raw DNs to at-satellite radiance (Equation 1) to at-sensor reflectance (Equation 2) in a multi-step process (Chander and Markham 2003).

$$(Eq. 1) \quad L_{\lambda} = \left(\frac{(LMAX_{\lambda} - LMIN_{\lambda})}{(QCALMAX - QCALMIN)} \right) (QCAL - QCALMIN) - LMIN_{\lambda}$$

Where:

L_{λ} = Spectral radiance at the sensor's aperture [W/(m² sr pm)]

Qcal = Quantized calibrated pixel value [DN]

Qcalmin = Minimum quantized calibrated pixel value corresponding to LMIN[^] [DN]

Qcalmax = Maximum quantized calibrated pixel value corresponding to LMAX) [DN]

LMIN _{λ} = Spectral at-sensor radiance that is scaled to Qcalmin [W/(m² sr μ m)]

LMAX _{λ} = Spectral at-sensor radiance that is scaled to Qcalmax [W/(m² sr μ m)]

$$(Eq. 2) \quad \rho_p = \frac{\pi \cdot L_{\lambda} \cdot d^2}{ESUN_{\lambda} \cdot \cos \theta_s}$$

Where:

ρ_p = unitless planetary reflectance;

L_{λ} = Spectral radiance at the sensor's aperture [W/(m² sr pm)]

d = earth–sun distance in astronomical units

ESUN _{λ} = mean solar exoatmospheric irradiances

θ_s = solar zenith angle in degrees

After the Landsat MSS images were resampled from 60 meters to 30 meters and all TOA-CDR raw DNs were scaled by a factor of 0.0001 (USGS 2014), the twelve images underwent dark object subtraction (DOS) (Chavez 1996) and were used in the classification process.

Image Classification

I performed a supervised minimum distance land cover classification on all twelve images using Erdas-Imagine (v.14). I selected training areas based on previous knowledge of the area and clear visual cues (e.g. surface mines, roads, grassland, forest). Signatures were sorted into three classes: Forest, Mining Activity/Urban, and Non-forest. The Forest class was

identified as any kind of forested area. I used 36 training sites for the classification. Mining Activity/Urban consisted of active mines, valley fills, reclaimed land, open grassland, roadways, and small urbanized areas. Because of the variety of land cover types I used twice as many training sites for this class than I did for the forest. The non-forest class was used to classify water and anything else that didn't fall into the other two classes; I used ten training sites for the classification.

I layerstacked the raw spectral bands and a number of derived products. Table 2 shows the spectral bands and indices used for each classification. To increase the separability of classes, I used various indices derived from the raw spectral bands. The Normalized Difference Vegetation Index (NDVI) is a measure of the ratio of near-IR to red reflectance:

$$(Eq. 3) \quad NDVI = (NIR - RED) / (NIR + RED)$$

The NDVI measures vegetation productivity, meaning that vegetated areas are highly reflective so it is useful in identifying highly vegetated and bare areas (Lyon et al. 1998, Peijun et al. 2010, Pettorelli et al. 2005, Sader et al. 2003).

Other indices like principle component analysis (PCA) and Tasseled-Cap (Brightness, Greenness, and Wetness) are also useful in monitoring land cover (Cohen et al. 1998, Collins and Woodcock 1996, Franklin et al. 2002, Myint et al. 2008, Townsend et al. 2009). Both PCA and Tasseled Cap reduce the number of components in an image so that fewer bands can be used. Another index, derived from Tasseled Cap is the Disturbance Index (DI) which is useful in monitoring forest and vegetation change (Healey et al. 2005, Masek et al. 2008). The DI is derived by rescaling the Tasseled Cap bands. For example, rescaling Brightness:

$$(Eq. 4) \quad B_r = (B - B_\mu) / B_\sigma$$

Where, B_{μ} is the mean brightness and B_{σ} is the standard deviation of the brightness index. Once Brightness, Greenness, and Wetness have been rescaled they are combined into a new equation:

$$(Eq. 5) \quad DI = B_r - (G_r + W_r)$$

Disturbed areas should then have high positive B_r and low negative G_r and W_r values. After a number of trials figuring out which combination of bands worked best, the first two principle components were used for all images, Tasseled Cap used on all but the OLI image, and the Disturbance Index used only in the MSS images.

Finally, I used image texture to help separate land cover types. Texture can differentiate plant communities as well as urban areas (Gallardo-Cruz et al. 2012, Stefanov et al. 2001). Texture of an image is measured by applying different mathematical formulas to the image and I found that when the mean Euclidean distance was applied it showed the best texture of roadways and mines for the red band in each year. So for the MSS images, I used the image texture of band 2 and the rest of the images I used the image texture of band 3.

Table 2. The bands and indices used in the supervised classification.

Year	Bands Used
1973 1976 1981	Spectral bands 1-4, Tasseled Cap, Principle Component 1 and 2, DI, NDVI, Texture-Band 2
1984 1987 1991 1995 1998 2001 2005 2008	Spectral bands 1-5 and 7, Tasseled Cap, Principle Component 1 and 2, NDVI, Texture-Band 3
2013	Spectral bands 1-7, Principle Component 1 and 2 , NDVI, Texture-Band 3

Once I classified all images, I found the overall area (ha) of each class for each year and the area of each class for the HUC 12 subwatersheds where *C. veteranus* was found historically.

Because change is localized and crayfish do not move great distances, it was important to look at the subwatersheds as a way to measure whether mining activity had an impact on the crayfish's decline over time.

Trend Analysis

To test for significant change in area over time I ran a Mann-Kendall (MK) test. The MK trend test was initially developed to analyze trends in water quality and is a useful test for seasonal and other time series data (De Beurs and Henebry 2004, Hirsh and Slack 1984, Yue and Wang 2004). The test assesses if there is trend over time and whether the trend is positive or negative. It is a non-parametric test and does not require normality; it assumes all observations are independent when no trend is present. I performed the MK test with XLStat (v. 2015.4.01.20780) in Excel (v. 14.0.7153.5000).

Accuracy Assessment of Image Classification

I used Erdas-Imagine to assess the accuracy of the classification. To measure the accuracy of the classified images, I created a total of 250 ground truth points. Points were created randomly, and with some user-defined points to ensure all classes were covered in the analysis. I assigned actual land cover class using the original Landsat images to measure. The accuracy assessment then produced an error matrix, accuracy totals, and Kappa coefficients, which I used to measure the accuracy of my classifications.

RESULTS

Land Cover Change

Over a forty year time span, the Upper Guyandotte River watershed has remained mostly forested with an ever increasing amount of mining activity (Table 3) (Appendix A). Forested land takes up over 90% of the land cover in any given year while mining activity or urbanization

accounts for about 2-8% of land cover over time; non-forest, consisting primarily of water, only consists of less than 1% of the land cover over time (Table 4).

Table 3. The area (ha) of each class over time in the Upper Guyandotte River watershed.

	Forest	Mining Activity/Urban	Non-forest	Total
1973	238,819.59	7,078.14	17.28	245,915.01
1976	241,679.16	4,218.21	17.64	245,915.01
1981	241,178.22	4,564.17	172.62	245,915.01
1984	235,726.74	9,753.48	434.79	245,915.01
1987	235,279.44	9,922.95	712.62	245,915.01
1991	234,624.78	10,999.62	290.61	245,915.01
1995	235,994.85	9,652.77	267.39	245,915.01
1998	232,774.47	12,721.23	419.31	245,915.01
2001	233,103.60	12,529.89	281.52	245,915.01
2005	231,934.05	13,749.48	231.48	245,915.01
2008	229,750.56	15,955.29	209.16	245,915.01
2013	225,021.06	20,589.75	304.20	245,915.01

Table 4. The percent area of each class over time.

	Forest	Mining Activity/Urban	Non-forest
1973	97.11	2.88	0.01
1976	98.28	1.72	0.01
1981	98.07	1.86	0.07
1984	95.86	3.97	0.18
1987	95.68	4.04	0.29
1991	95.41	4.47	0.12
1995	95.97	3.93	0.11
1998	94.66	5.17	0.17
2001	94.79	5.10	0.11
2005	94.31	5.59	0.09
2008	93.43	6.49	0.09
2013	91.50	8.37	0.12

While the mining activity/urban class consists of various kinds of land cover, from roadways to small towns to mines and valley fills, the greatest changes within this class are clearly due to surface mining. It is easy to see this change from the decade of 1991-2001 (Figure 2). The mines have distinct, irregular shapes and visibly show the increased mining activity. It is

also possible to see where mines have been reclaimed because they change classes from Mining Activity/Urban to Forest.

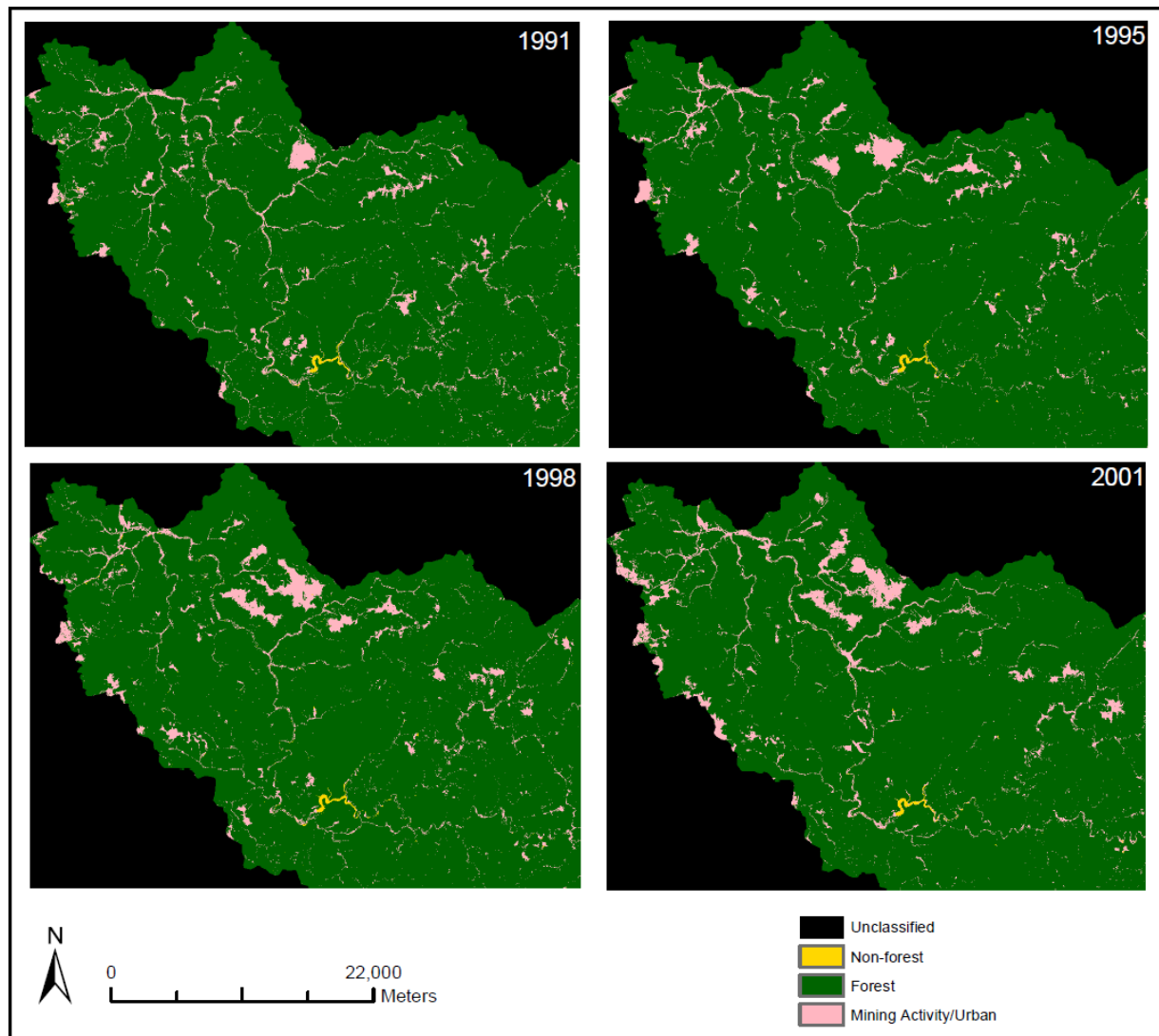


Figure 2. Land use changes from 1991-2001. It is easy to spot the changes in landscape due to mining in the northern part of the watershed.

With non-forest taking up less than 1% of the area in any given year, land cover changes occur only between forest and mining. A distinct trend of forest loss and increased mining activity can be seen over time (Figure 3 and 4). There was an overall 5.61% decrease in forested area and a 5.49% increase in mining activity from 1973 to 2013. There was an overall 5.5%

decrease in forested area from 1973 to 2013. The Mann-Kendall tests shows that the downward trend in forest area is significant (Kendall's tau = -0.818, $p < 0.0001$), as is the upward trend of mining activity (Kendall's tau = 0.818, $p < 0.0001$).

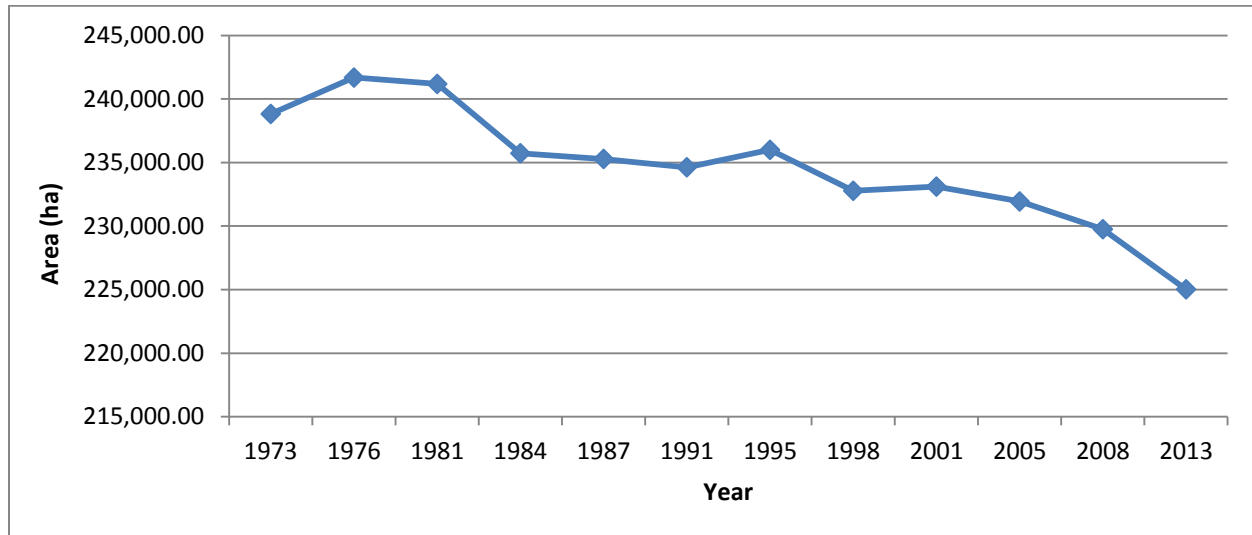


Figure 3. The area (ha) of forest land cover over time. There was a distinct downward trend of forested area in the Upper Guyandotte River watershed.

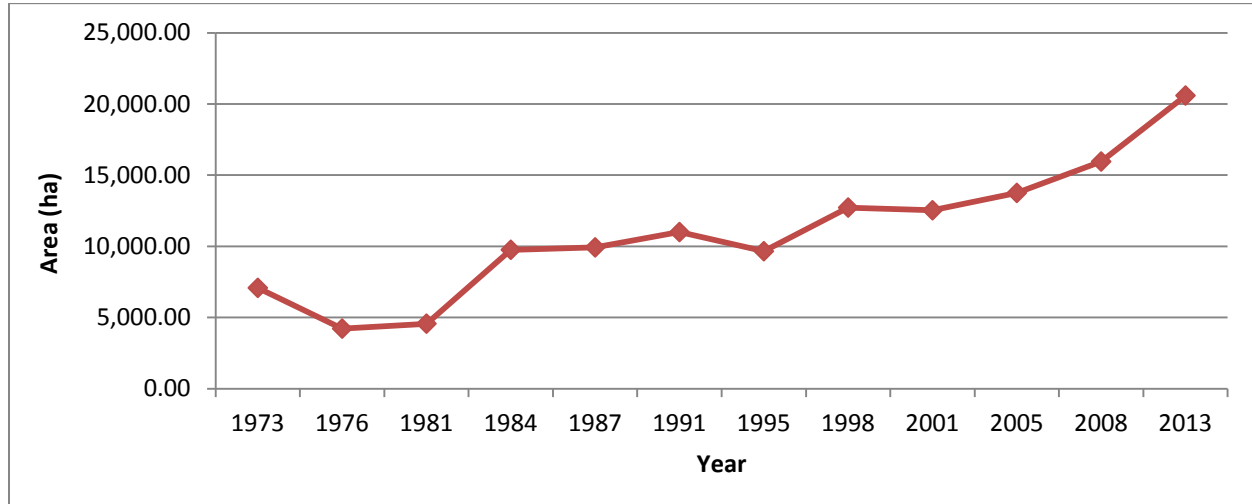


Figure 4. The area (ha) of mining activity/urban land cover over time. There was a distinct upward trend of disturbed area in the Upper Guyandotte River watershed.

Area of Subwatersheds

While the total area within the Upper Guyandotte watershed significantly changed over forty years, the overall change may not show whether mining had an effect on the decline of

Cambarus veteranus. By looking at the area of the subwatersheds where the crayfish has historically been found, greater changes in area can be more evident and indicate a cause for the crayfish's decline. The total area of each watershed varies (Figure 5), but some watersheds experienced greater changes in area over time than others (Figures 6-12).

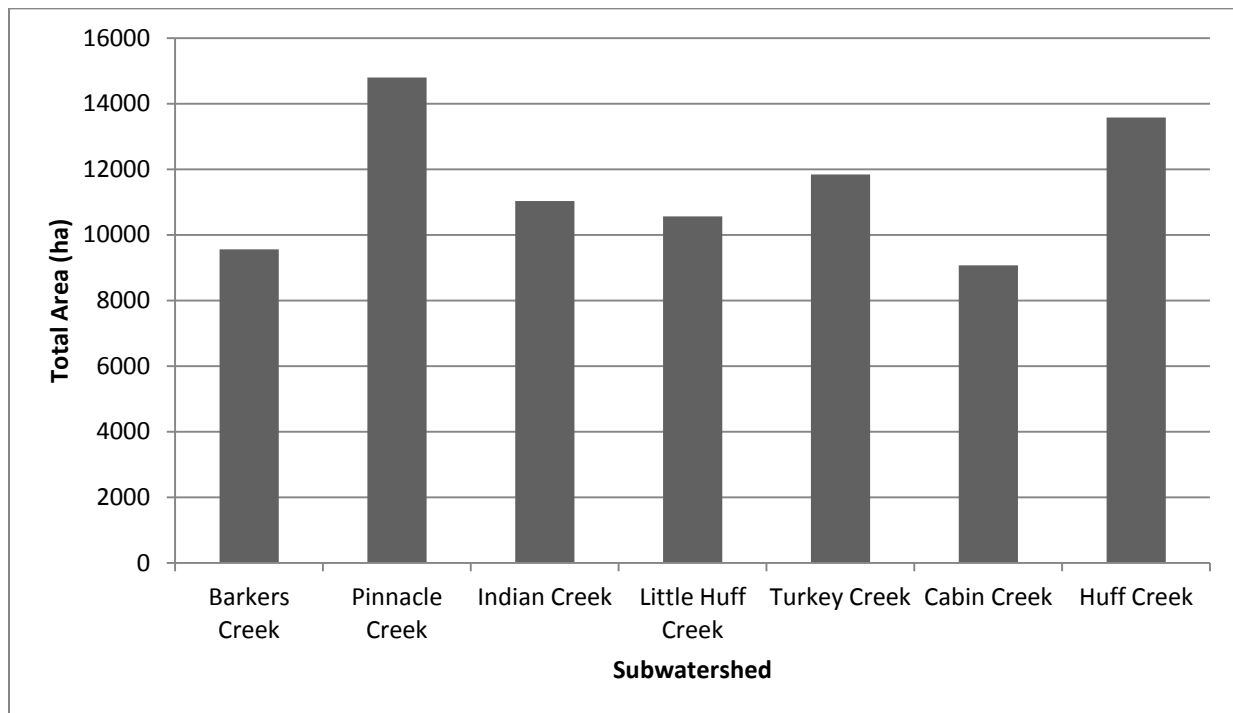


Figure 5. The total area (ha) of each subwatershed where *C. veteranus* has historically been found.

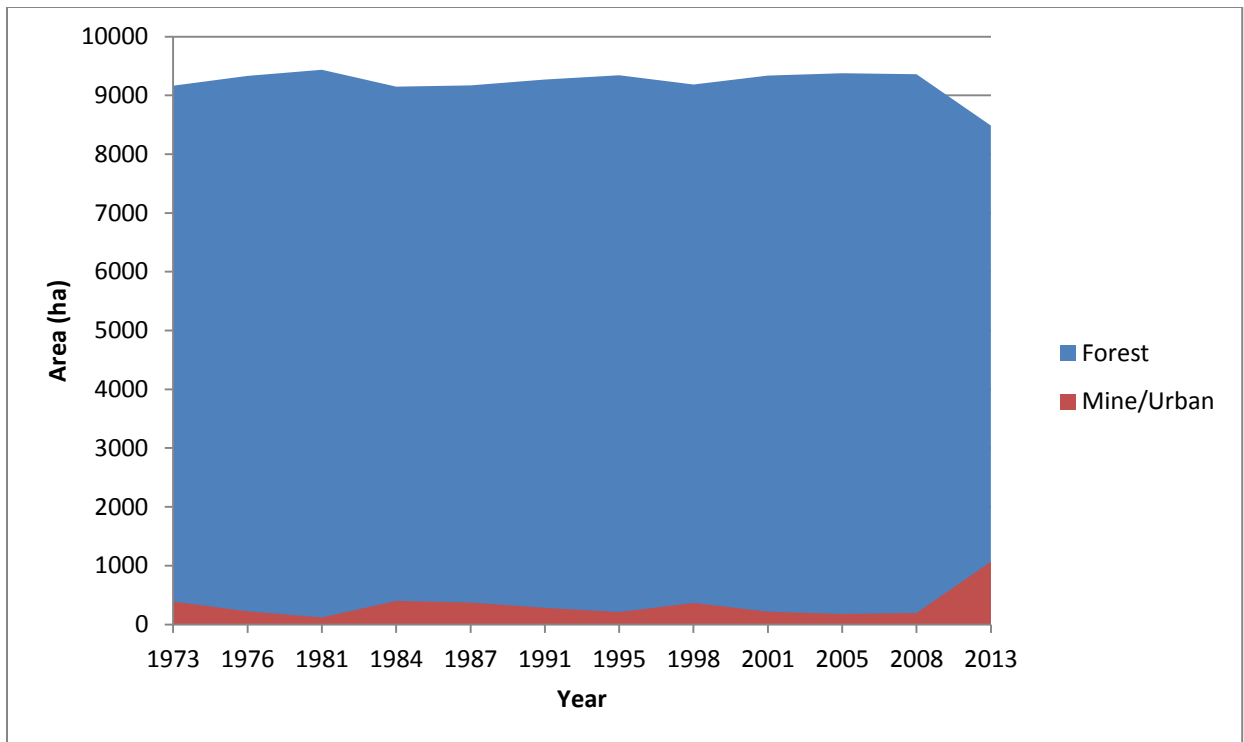


Figure 6. The area of Barkers Creek HUC 12 subwatershed. The area did not experience a significant change in forested area over time (Kendall's tau: 0.152, $p = 0.293$).

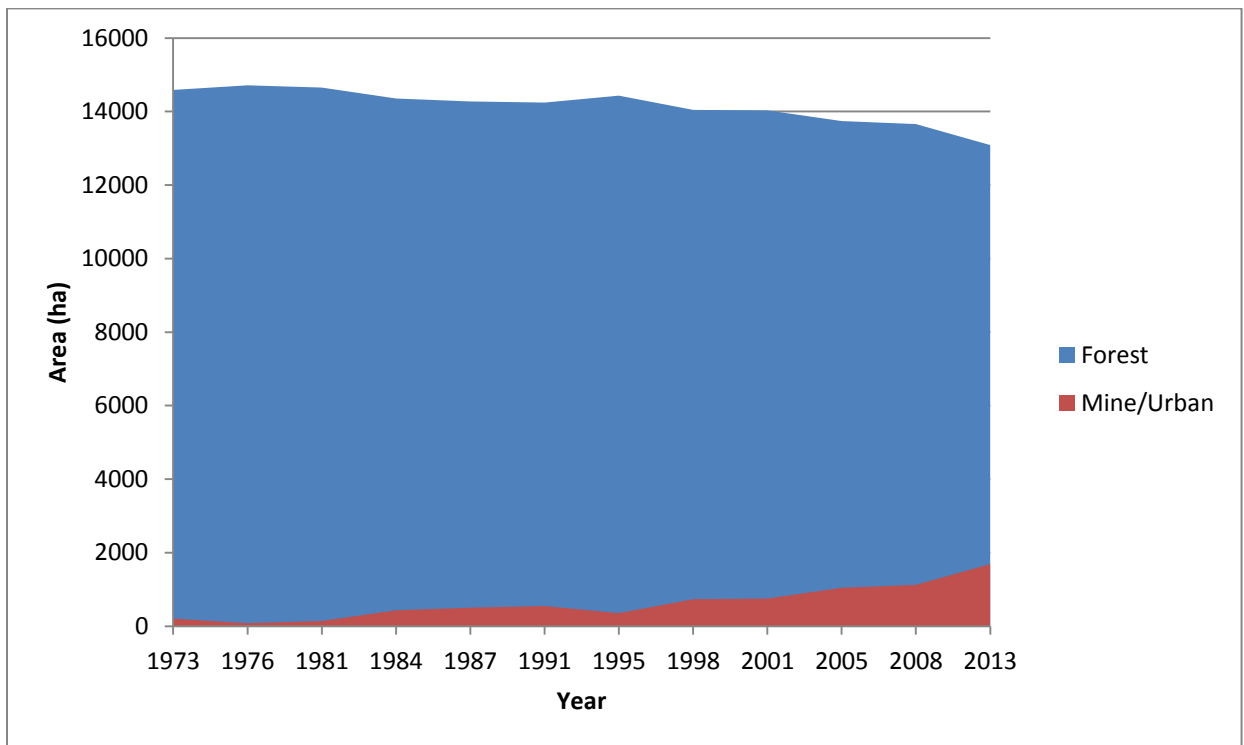


Figure 7. Area of Pinnacle Creek HUC 12 subwatershed. The area did experience a significant decline in forested area over time (Kendall's tau: -0.848, $p < 0.0001$).

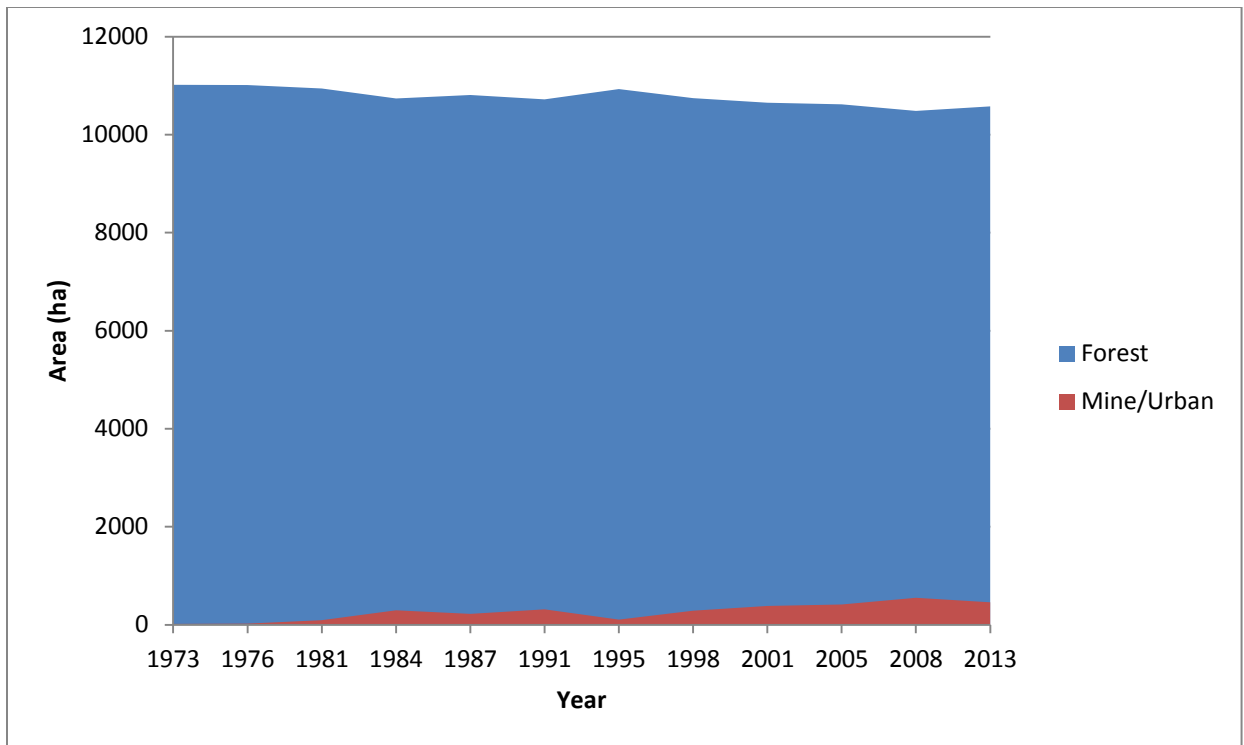


Figure 8. Area of Indian Creek HUC 12 subwatershed. The area did experience a significant decline in forested area over time (Kendall's tau: -0.788, $p < 0.0001$).

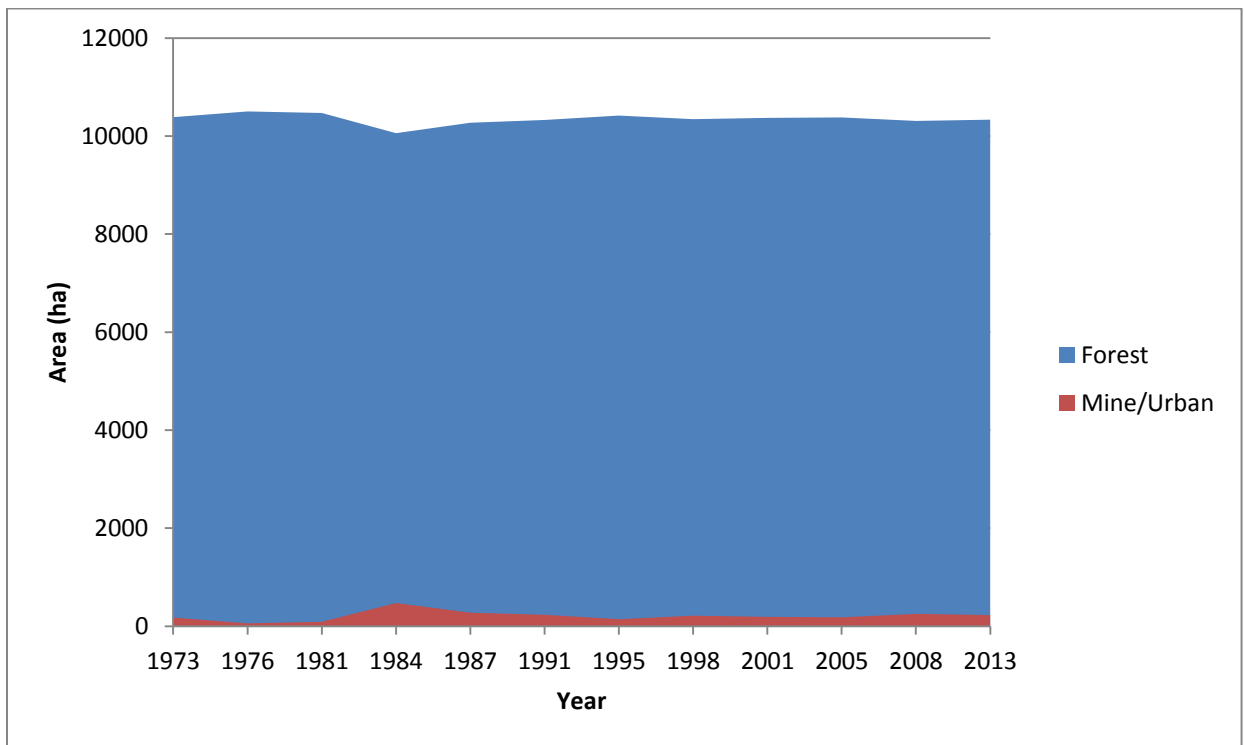


Figure 9. Area of Little Huff Creek HUC 12 subwatershed. The area did not experience a significant change in forested area over time (Kendall's tau: -0.182, $p = 0.069$).

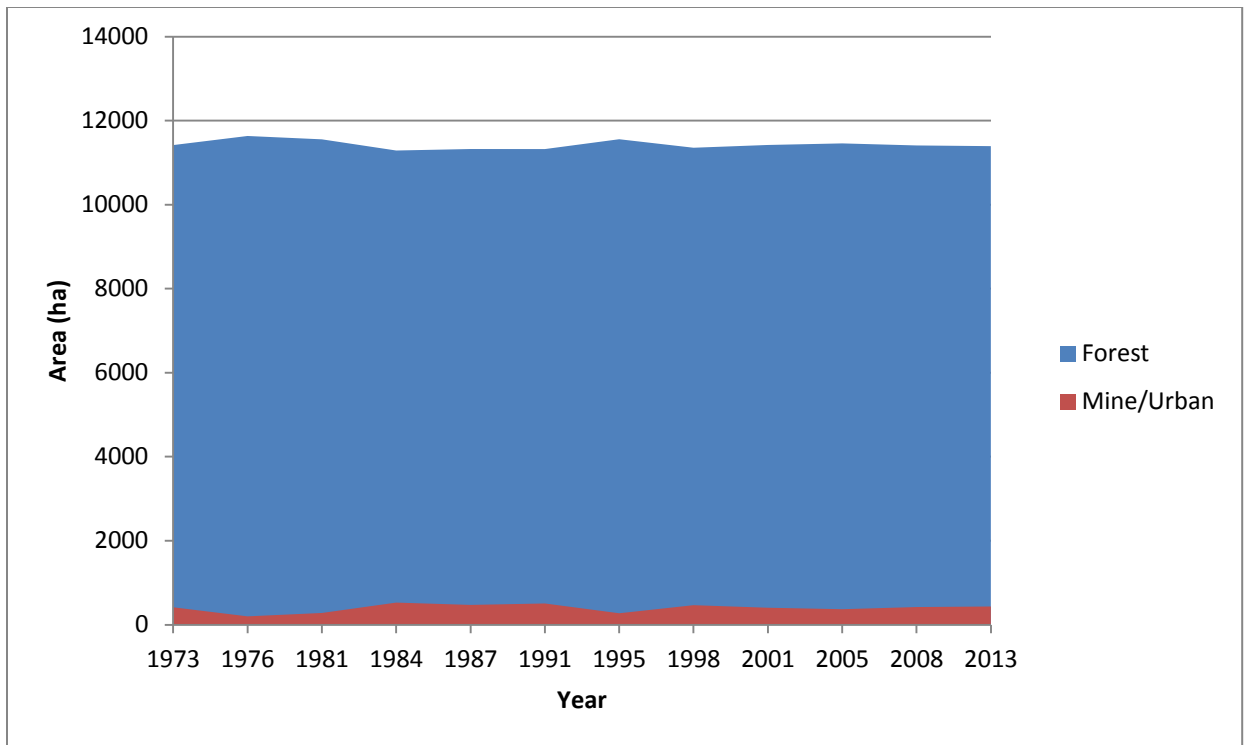


Figure 10. Area of Turkey Creek HUC 12 subwatershed. The area did not experience a significant change in forested area over time (Kendall's tau: -0.062, $p = 0.559$).

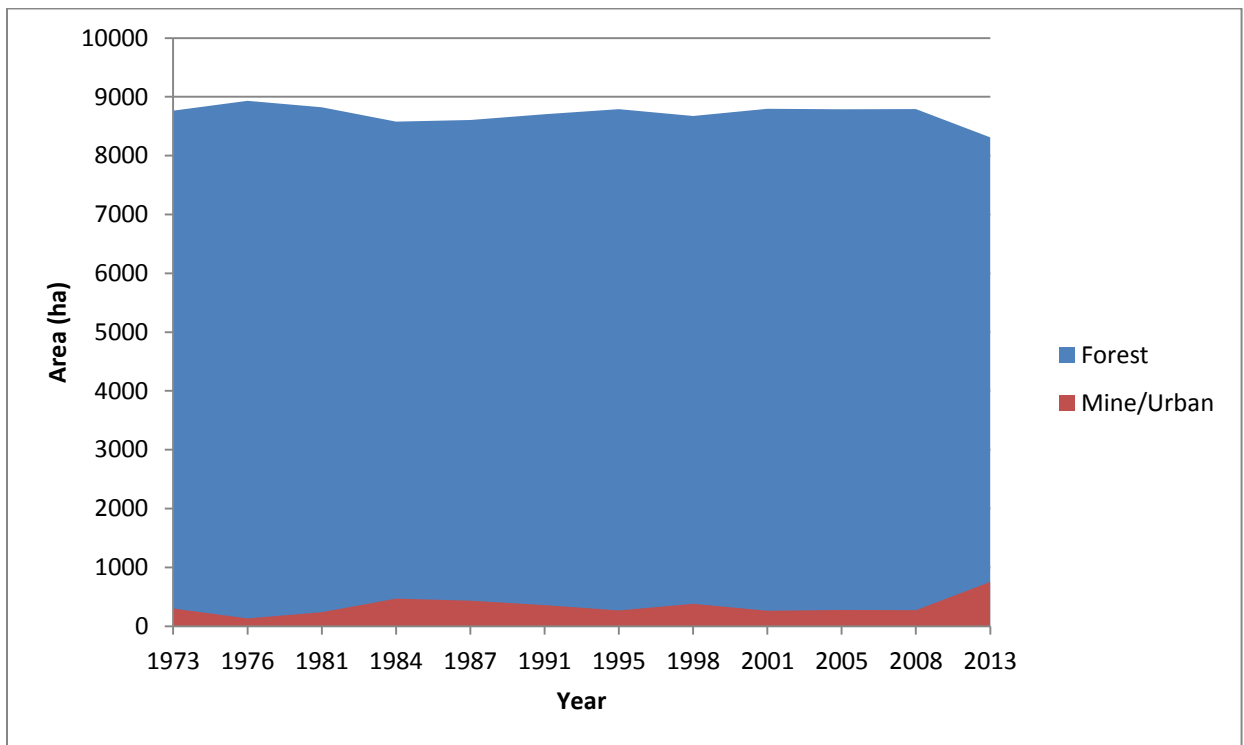


Figure 11. Area of Cabin Creek HUC 12 subwatershed. The area did not experience a significant change in forested area over time (Kendall's tau: -0.121, $p = 0.316$).

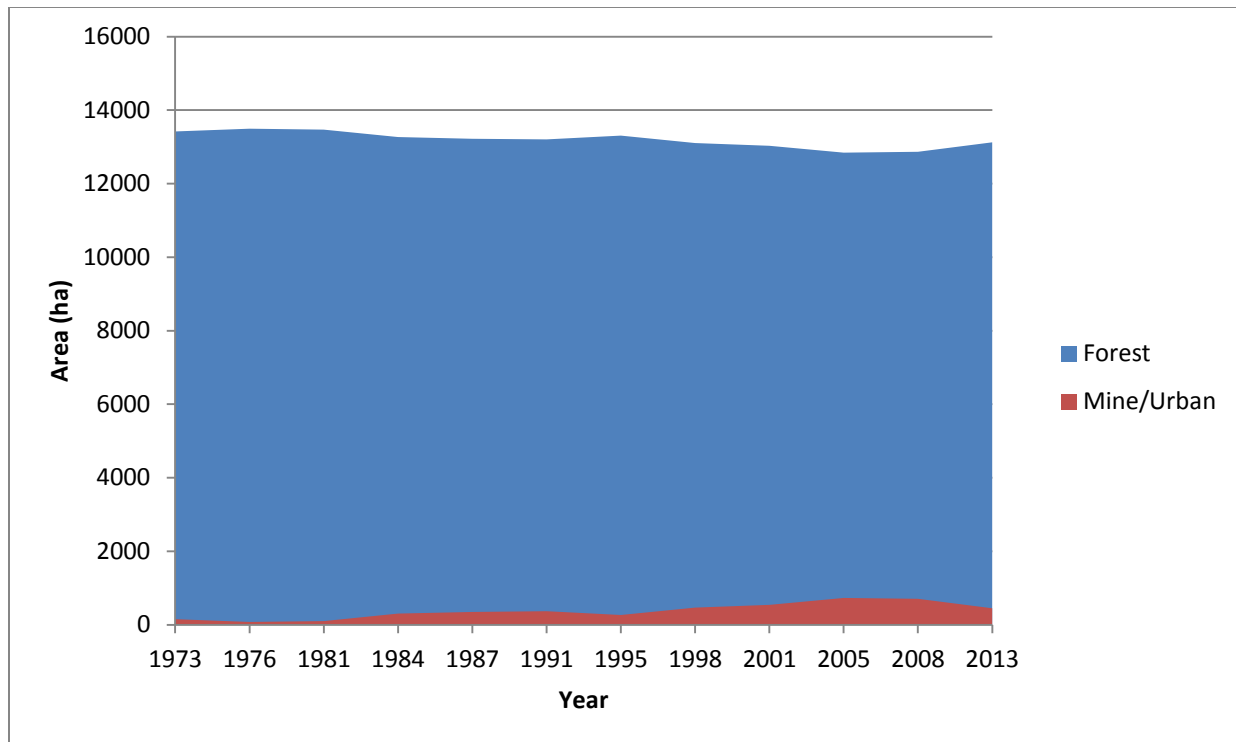


Figure 12. Area of Huff Creek HUC 12 subwatershed. The area did experience a significant decline in forested area over time (Kendall's tau: -0.697, $p < 0.0001$).

Pinnacle Creek experienced the greatest forest loss overall, going from 14,588 to 13,087 hectares and Turkey Creek experienced the least loss, going from 11,418 to 11,392 hectares (Table 5) (Appendix B). The crayfish survey in 1988-89 (Jezerinac et al. 1995) found *C. veteranus* in only three of the seven subwatersheds in which it had previously had been documented: Pinnacle, Huff, and Indian Creeks. These three watersheds that experienced significant change in area over time were the ones from the 1989 survey (Pinnacle Creek: Kendall's tau: -0.848, $p < 0.0001$; Indian Creek: Kendall's tau: -0.788, $p < 0.0001$; Huff Creek: Kendall's tau: -0.697, $p < 0.0001$). The other four watersheds did not show a significant change in trend over time for forested area (Barkers Creek: Kendall's tau: 0.152, $p = 0.293$; Little Huff Creek: Kendall's tau: -0.182, $p = 0.069$; Turkey Creek: Kendall's tau: -0.062, $p = 0.559$; Cabin Creek: Kendall's tau: -0.121, $p = 0.316$).

Table 5. The area (ha) of forest and mining activity classes for each watershed over time.

	Barkers Creek	Pinnacle Creek	Indian Creek	Little Huff Creek	Turkey Creek	Cabin Creek	Huff Creek
Forest							
1973	9165.15	14587.74	11016.72	10385.55	11418.21	8765.37	13419.63
1976	9331.65	14712.3	11011.59	10502.55	11634.48	8932.68	13494.42
1981	9435.78	14651.55	10941.21	10471.32	11554.38	8822.79	13469.31
1984	9148.77	14354.1	10737.72	10059.21	11288.25	8578.98	13267.62
1987	9170.1	14273.55	10808.82	10271.88	11324.07	8606.79	13220.28
1991	9269.91	14243.13	10719.45	10328.67	11322.99	8704.53	13203.54
1995	9342.54	14431.41	10929.33	10418.58	11557.08	8790.66	13306.68
1998	9184.86	14044.23	10744.65	10344.78	11354.85	8674.74	13104.27
2001	9336.69	14030.55	10650.69	10370.88	11420.73	8797.32	13029.75
2005	9377.01	13740.57	10618.47	10380.51	11457.81	8788.77	12842.82
2008	9359.82	13657.95	10483.65	10309.23	11409.39	8792.01	12866.58
2013	8486.73	13087.26	10576.17	10334.61	11392.56	8311.41	13123.98
Mining Activity/Urban							
1973	389.43	205.2	17.73	176.13	415.98	300.51	151.83
1976	223.29	80.28	23.31	58.41	200.07	132.48	76.59
1981	118.8	141.03	93.69	90.36	280.53	238.41	99.72
1984	400.05	432.36	295.29	472.32	527.49	469.26	304.29
1987	372.96	501.75	222.3	275.4	472.23	434.07	348.48
1991	282.51	547.38	314.82	232.83	506.88	358.47	368.91
1995	211.5	354.69	105.21	142.92	274.05	267.75	265.5
1998	365.85	731.88	286.92	214.2	466.38	381.42	466.56
2001	217.26	750.6	383.85	190.8	405.45	262.53	541.44
2005	177.57	1044.09	413.82	181.17	370.35	276.48	729
2008	194.67	1123.92	550.08	252.09	421.38	272.7	706.14
2013	1067.13	1687.05	458.28	226.98	434.7	753.21	448.74

Land Cover Accuracy Assessment

Accuracy was high for the land cover classifications, with overall accuracy over 90% or better the majority of the time (Table 6). Forest was mapped at a very high level of accuracy across the forty year time span, with 2013 having the lowest user's accuracy for forest at 87.34%. Non-forest was less accurate as the other two classes overall, but classified highly accurately in most years. Due to the small amount of area of non-forest in 1973 and 1976, the

class had 0% accuracy. Any pixels that were labeled as non-forest in the assessment were not correctly classified. With the class being of little concern to land cover change, the poor accuracy is not a large worry in the early years for this study. Non-forest had the worst user's accuracy in 1987, correctly being classified only 60% of the time, but was highly accurate 85-100% in all other years. The mining activity/urban class was classified highly accurately over most years (83-100%), with 2013 having the worst producer's accuracy of 72.62%. The user's accuracy was more accurate than the producer's accuracy for mining activity/urban land cover but the Kappa coefficients were the highest out of the three classes in almost all years.

Table 6. Percent producer's and user's accuracy of mapped cover classes over time and Kappa coefficient for each class in each year.

	Overall Accuracy	Overall Kappa Coefficient	Class	Producer's Accuracy	User's Accuracy
1973	91.60%	0.8238	Non-forest	---	---
			Forest	98.03%	90.85%
			Mining Activity/Urban	83.33%	98.77%
1976	91.20%	0.8302	Non-forest	---	---
			Forest	90.58%	93.98%
			Mining Activity/Urban	91.96%	98.10%
1981	95.60%	0.9221	Non-forest	90.00%	90.00%
			Forest	98.41%	95.38%
			Mining Activity/Urban	93.27%	97.00%
1984	92.00%	0.8519	Non-forest	100.00%	85.71%
			Forest	98.58%	89.68%
			Mining Activity/Urban	82.95%	98.65%
1987	93.60%	0.8899	Non-forest	100.00%	60.00%
			Forest	95.08%	96.67%
			Mining Activity/Urban	90.91%	100.00%
1991	96.80%	0.9257	Non-forest	96.00%	92.31%
			Forest	99.44%	97.28%
			Mining Activity/Urban	86.67%	97.50%

1995	94.80%	0.8843	Non-forest	100.00%	86.21%
			Forest	98.86%	95.58%
			Mining Activity/Urban	78.00%	97.50%
1998	95.20%	0.9019	Non-forest	92.00%	88.46%
			Forest	100.00%	94.77%
			Mining Activity/Urban	83.87%	100.00%
2001	97.20%	0.9474	Non-forest	100.00%	92.59%
			Forest	98.05%	97.42%
			Mining Activity/Urban	94.37%	98.53%
2005	95.2%	0.9150	Non-forest	96.00%	88.89%
			Forest	97.81%	95.04%
			Mining Activity/Urban	90.91%	97.56%
2008	96.00%	0.9320	Non-forest	100.00%	80.00%
			Forest	96.69%	97.50%
			Mining Activity/Urban	94.29%	99.00%
2013	88.80%	0.7946	Non-forest	92.00%	85.19%
			Forest	97.87%	87.34%
			Mining Activity/Urban	72.62%	93.85%

DISCUSSION

Land cover change was expected for the Upper Guyandotte River watershed given the history of mining within the area. The supervised classification mapped an overall 5.5% decrease in forested area. The forest was lost to either mining or roadway. There are not many large urban areas within the watershed so most of what got classified as mining activity/urban was either a roadway or mining activity (e.g. active surface mine, valley fill, refuse structure). The change from forest to mine/road has only increased with time. Roads create pollution in the form of sediment with mines acidifying waters, increasing ion concentrations, releasing toxic metals into the waterways, and burying headwaters with valley fills (Bernhardt and Palmer 2011, Bernhardt

et al. 2012, Pond et al. 2008, U.S. EPA 2011). An increase in mining activity will have a negative impact on anything living downstream, including *Cambarus veteranus*.

The change in the area for the Upper Guyandotte River watershed was significant, but the change in subwatersheds reveals more about the impact of mining on the decline of *C. veteranus* than the overall loss of forest. Since *C. veteranus* has not been found in some of the watersheds since 1947 or even 1900, it is difficult to determine exactly when the crayfish stopped occurring within those watersheds. The 1988-89 survey though showed *C. veteranus* in three subwatersheds from which I could evaluate whether mining had an impact on crayfish decline. Those three subwatersheds underwent significant decline in forested area from 1973 to 2013. In two out of the three subwatersheds, *C. veteranus* is no longer found. With mining significantly increasing over time within the three subwatersheds and the environmental degradation mining causes it is likely that mining has caused *Cambarus veteranus* to become nearly extinct within its native West Virginia range.

While overall accuracy was high for all years, there was still some confusion between classes in the classified images. Some of this confusion within the classification is most likely due to mixed pixels. For example, vegetation overhangs many of the smaller roads in the watershed, so roads seem patchy within the classification. Reclaimed mine land also introduces error. Reclaimed land was included in the mining activity/urban land cover class because reclaimed lands are often hydrologically different to surrounding forest areas and have different vegetation composition as well (Holl 2002, Miller and Zegre 2014, Simmons et al. 2008, Wiley et al. 2001). While most reclaimed mines did get classified as mining activity in each year, reclaimed mines caused confusion between mining activity and forest. The edges of surface mines also might have created mixed pixels as mines just abruptly stop at the edge of the forest

with no real transition. The non-forest land cover class was highly accurate for most years, but 1973 and 1976 saw poor accuracy due to a lack of open water. The class was used to classify mainly water bodies and the R. D. Bailey Lake, which was constructed in 1980 (Beanblossom 2010), is the largest water body that can be seen within the Landsat images. Thus, it is not surprising that there was poor accuracy for the non-forest class in those years because there was no lake yet to classify.

While most of the original Landsat images had little cloud cover, atmospheric interference also probably had an impact on classification accuracy. Cloud cover masks would have been helpful for some images, like 1976 and in particular 2013, where cloud cover interfered the most with the classification process. Because of the cloud cover in 2013, mining activity was overestimated and adding another image to the time series would help clarify how much land cover actually changed. The cloud cover though did not change the fact that there was a downward trend of forest loss within the watershed over forty years.

Supervised classification of the Upper Guyandotte River watershed revealed that mining has caused a significant change in the land cover over the past forty years from 1973-2013. Using Landsat imagery is a useful resource in monitoring land cover change with high accuracy over a large area and could be useful in continuing to monitor the watershed as surface mining is not decreasing within the watershed. With the increase of mining activities, *Cambarus veteranus* has nearly gone extinct and without further protection and monitoring, this endangered crayfish will be lost in West Virginia.

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Appendix A: Classified Images

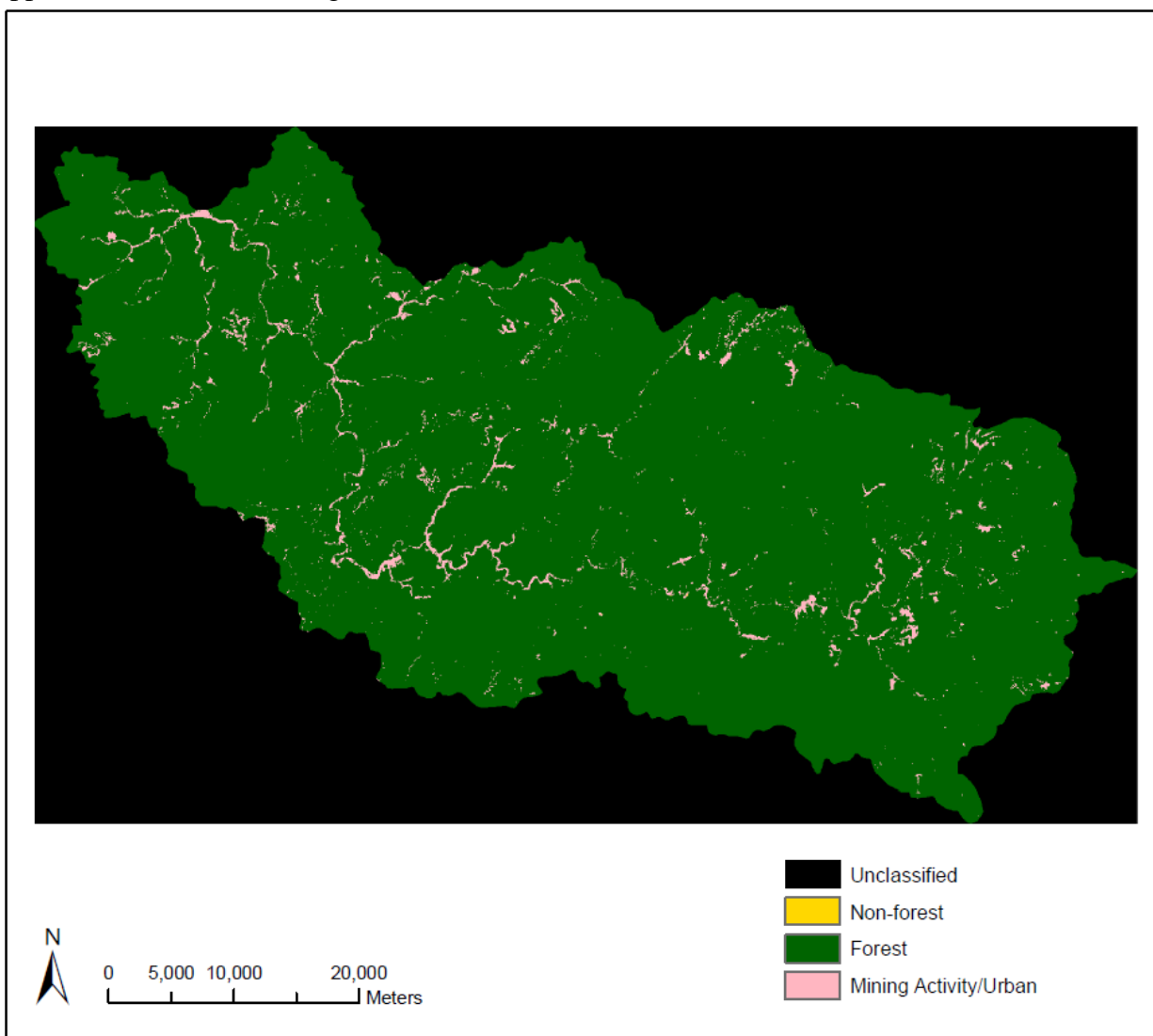


Figure 2.1. Classified image of September 1973.

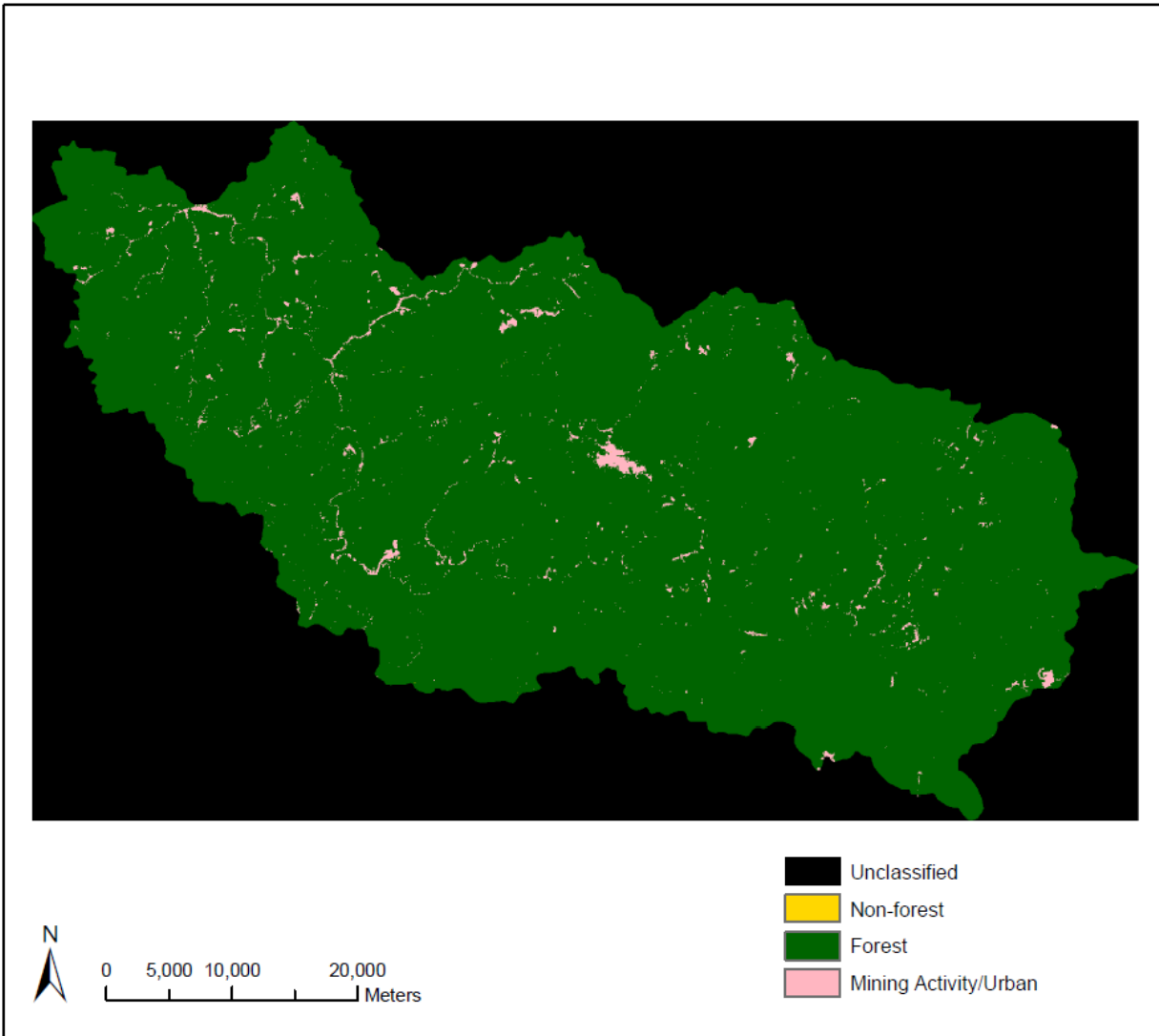


Figure 2.2. Classified image of September 1976.

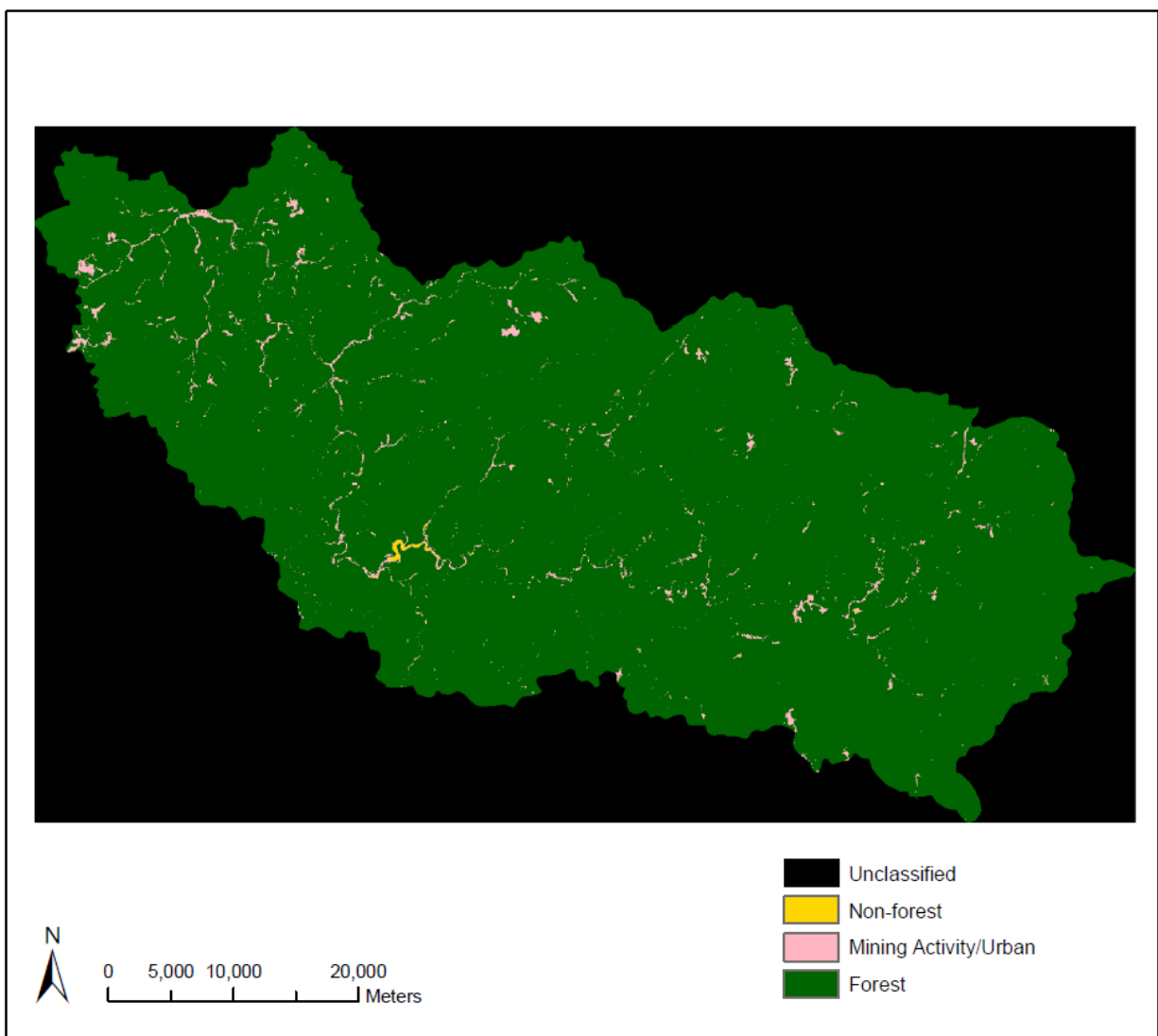


Figure 2.3. Classified image of September 1981.

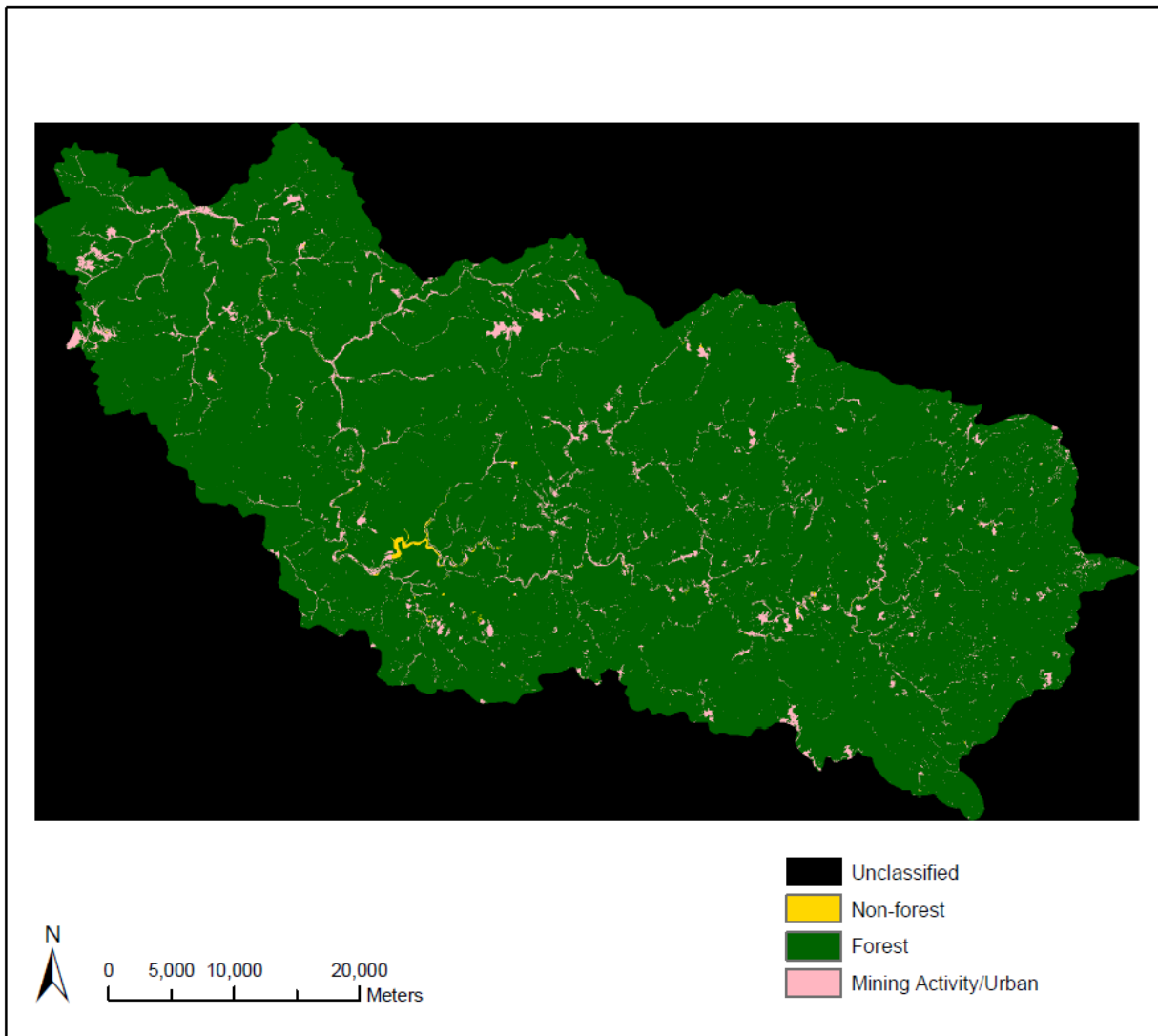


Figure 2.4. Classified image of September 1984.

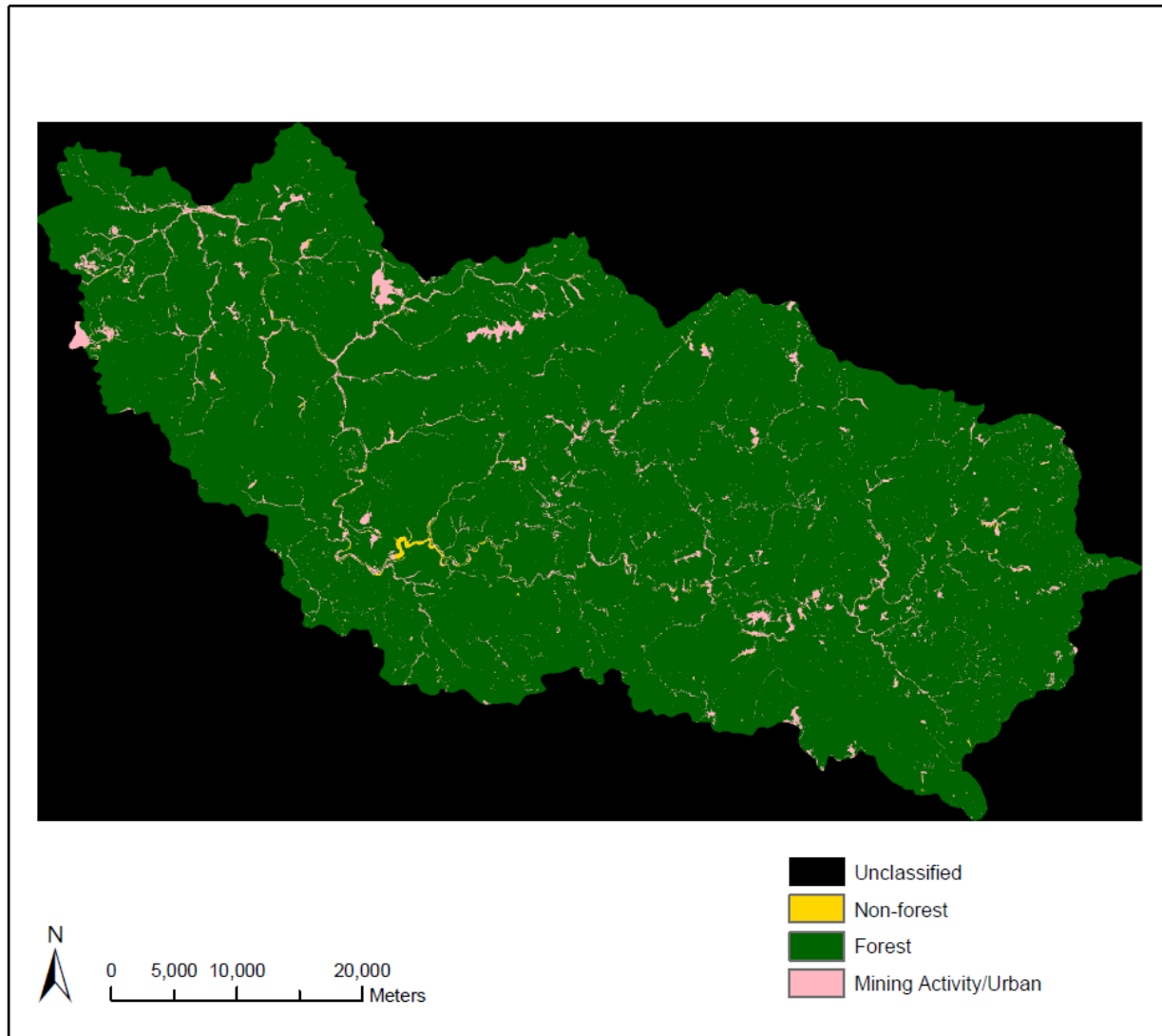


Figure 2.5. Classified image of September 1987.

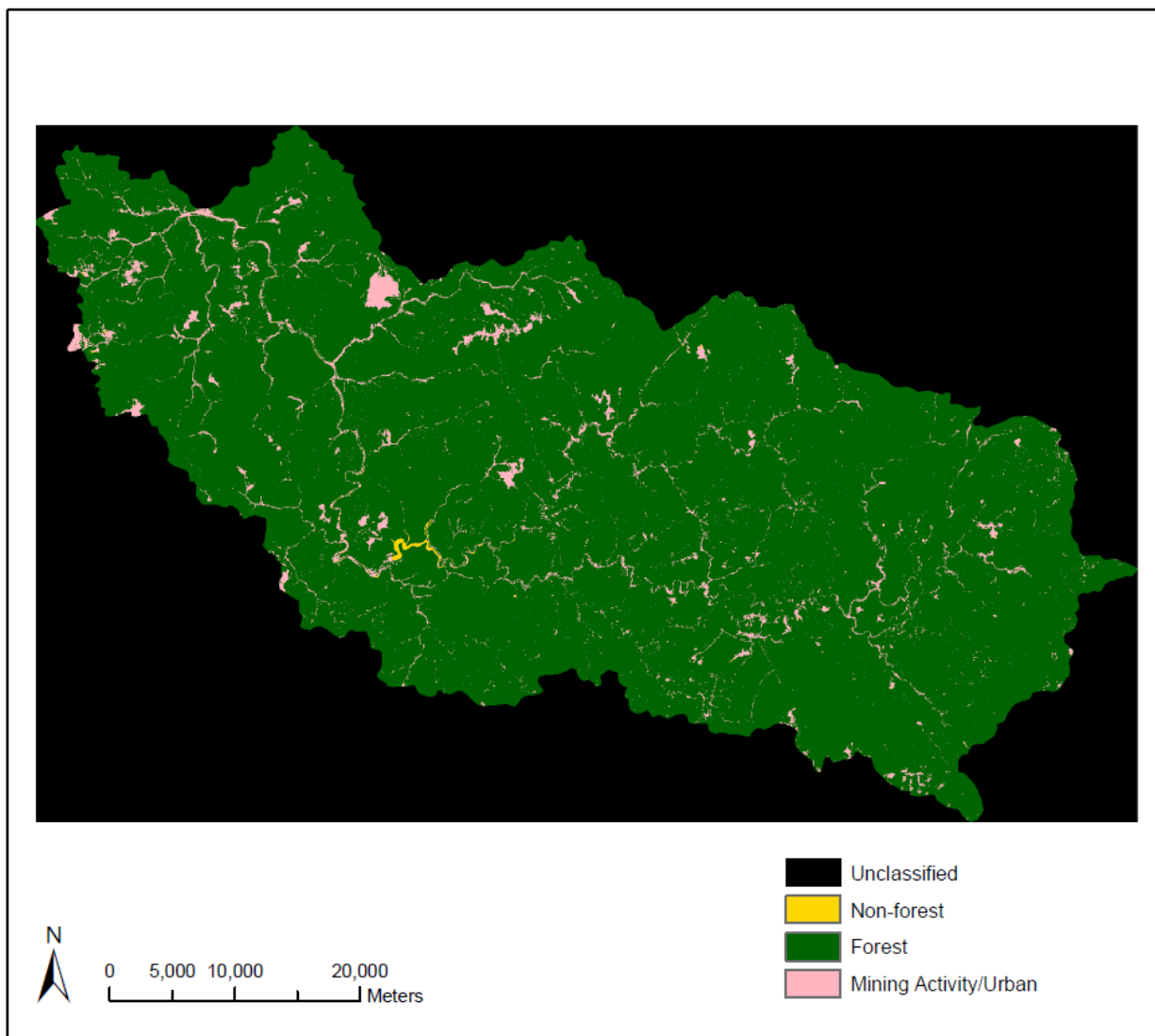


Figure 2.6. Classified image of September 1991.

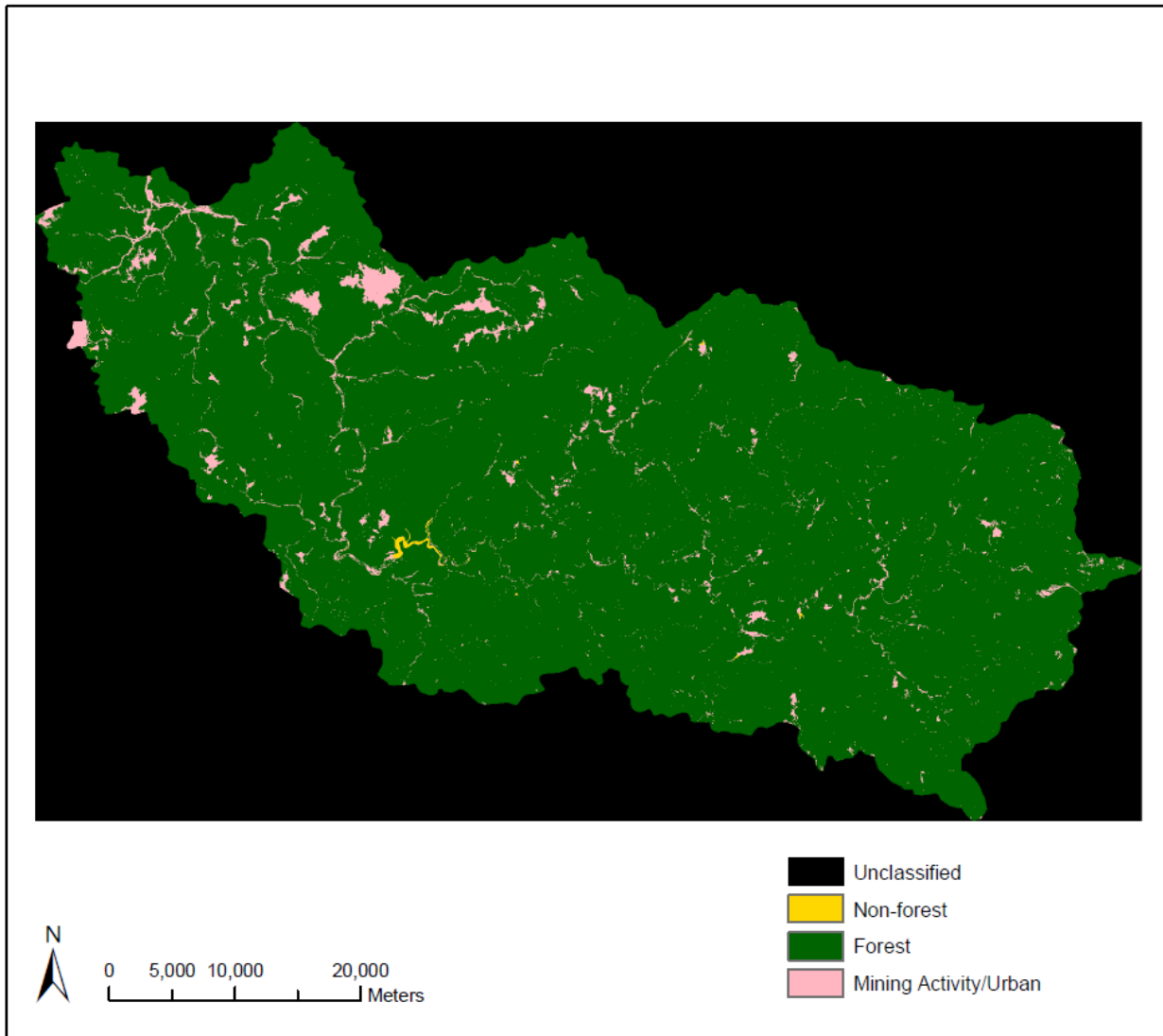


Figure 2.7. Classified image of August 1995.

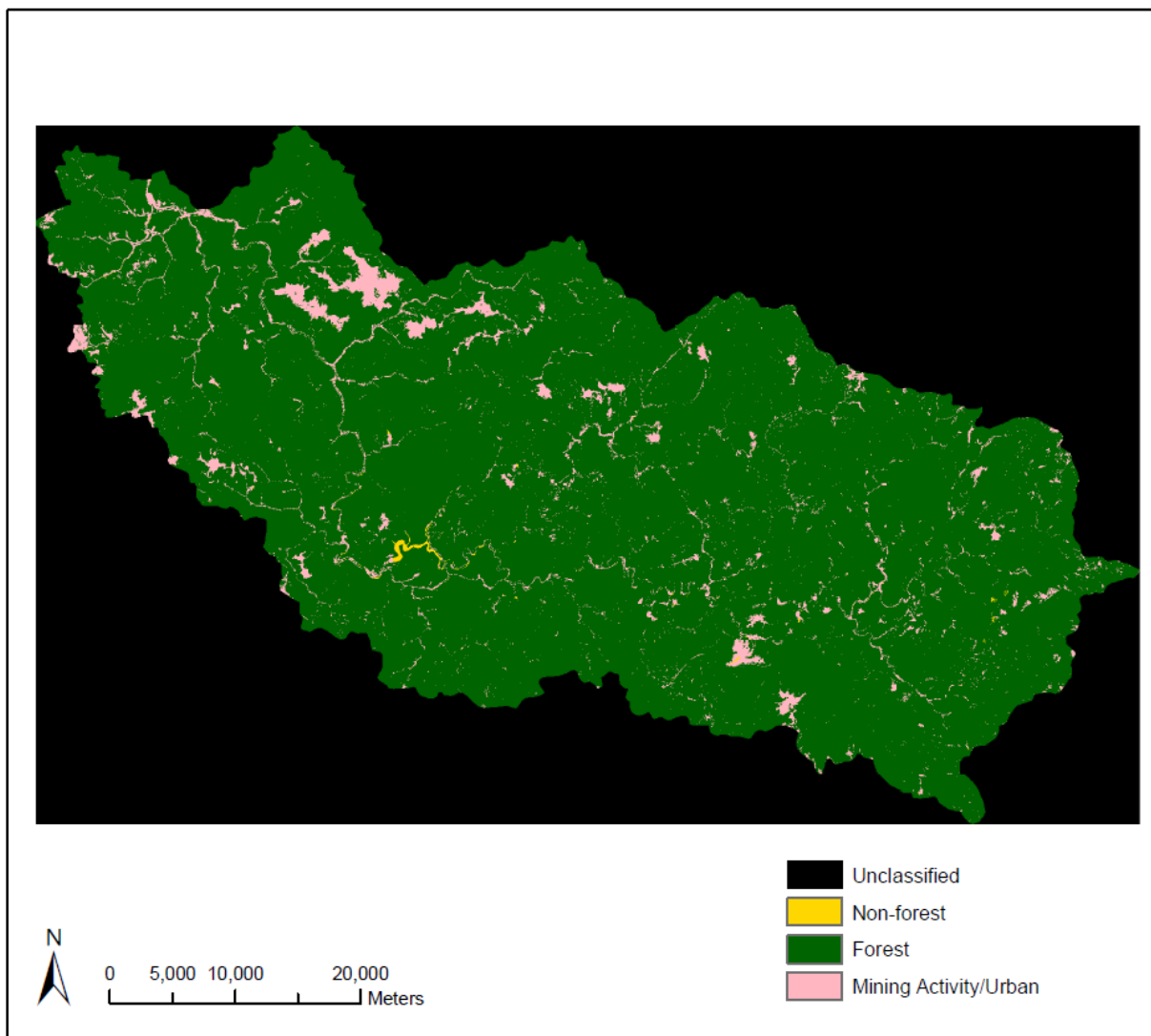


Figure 2.8. Classified image of September 1998.

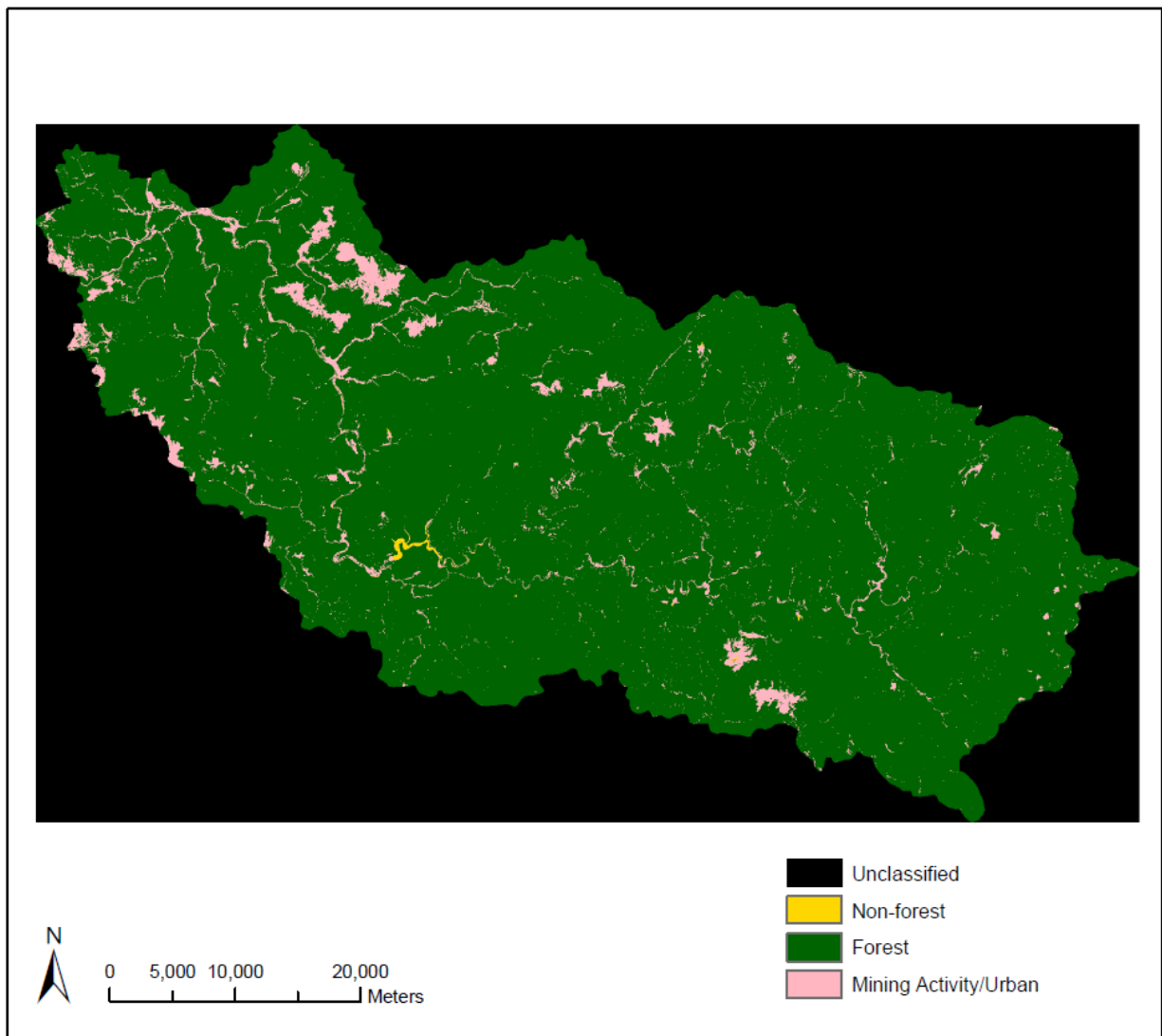


Figure 2.9. Classified image of September 2001.

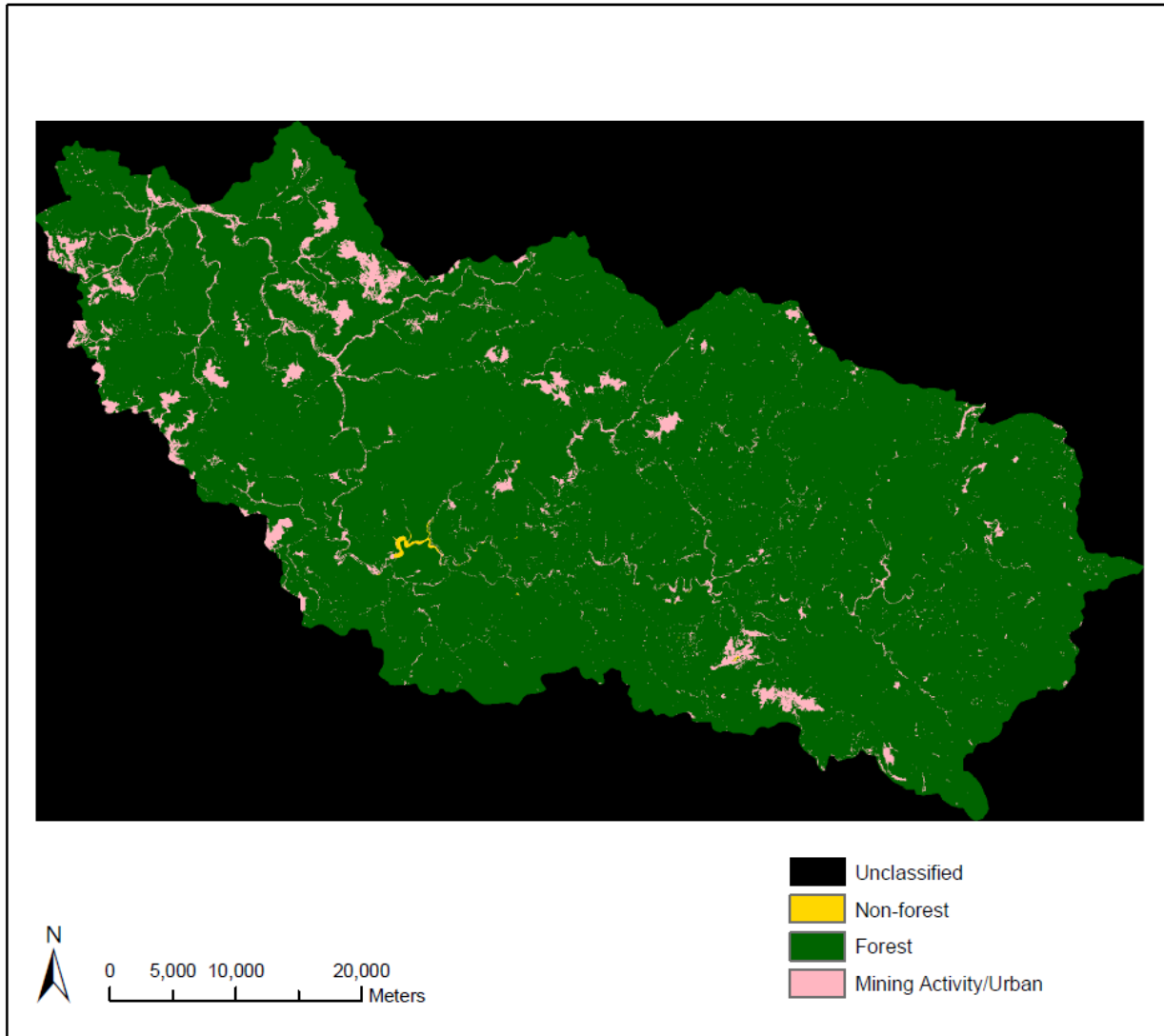


Figure 2.10. Classified image of September 2005.

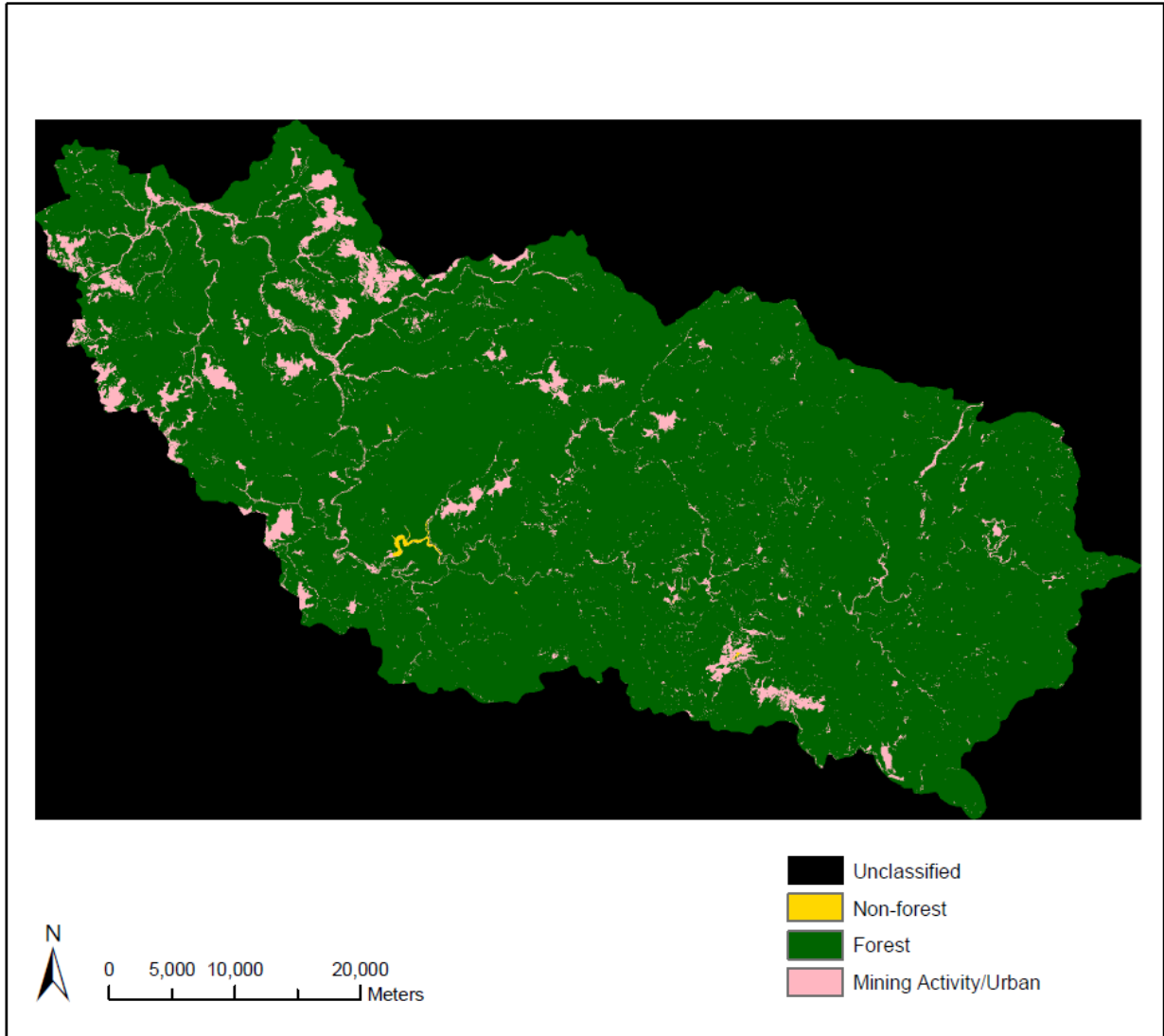


Figure 2.11. Classified image of September 2008.

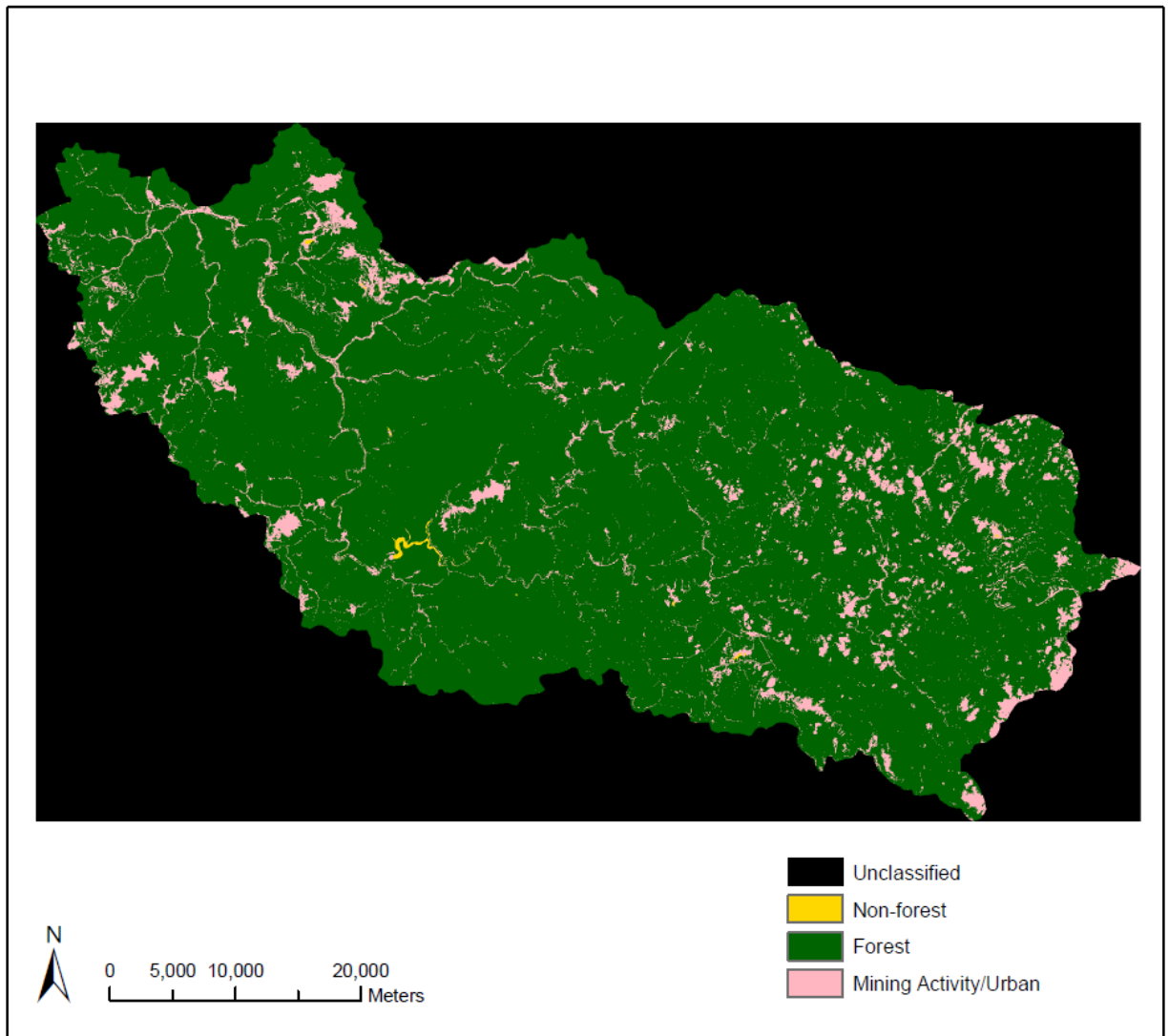


Figure 2.12. Classified image of September 2013.

Appendix B: Area of Pinnacle Creek HUC 12 subwatershed over time.

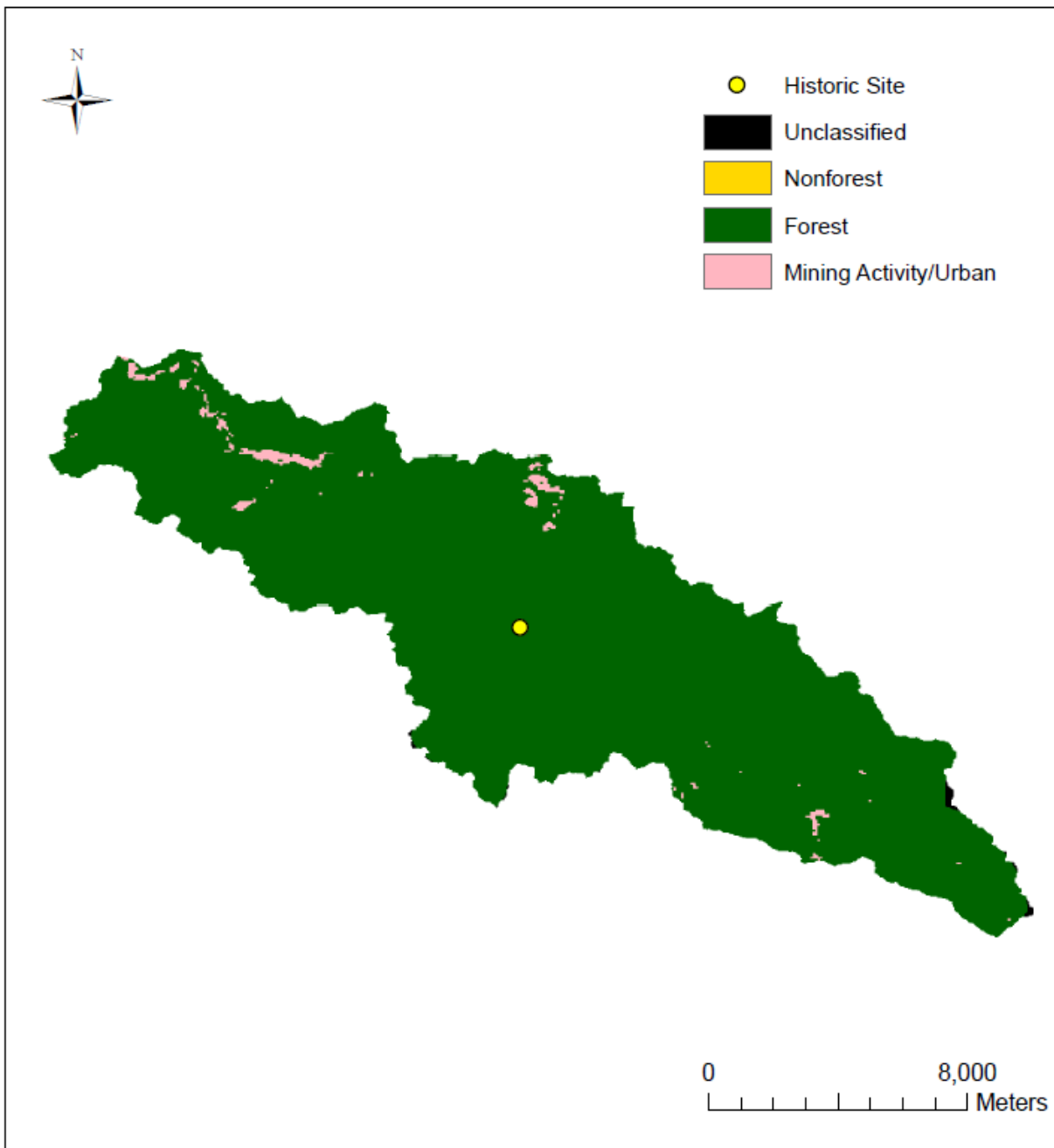


Figure 3.1. Classified image of Pinnacle Creek HUC 12 subwatershed in 1973 with the historic site of *Cambarus veteranus*.

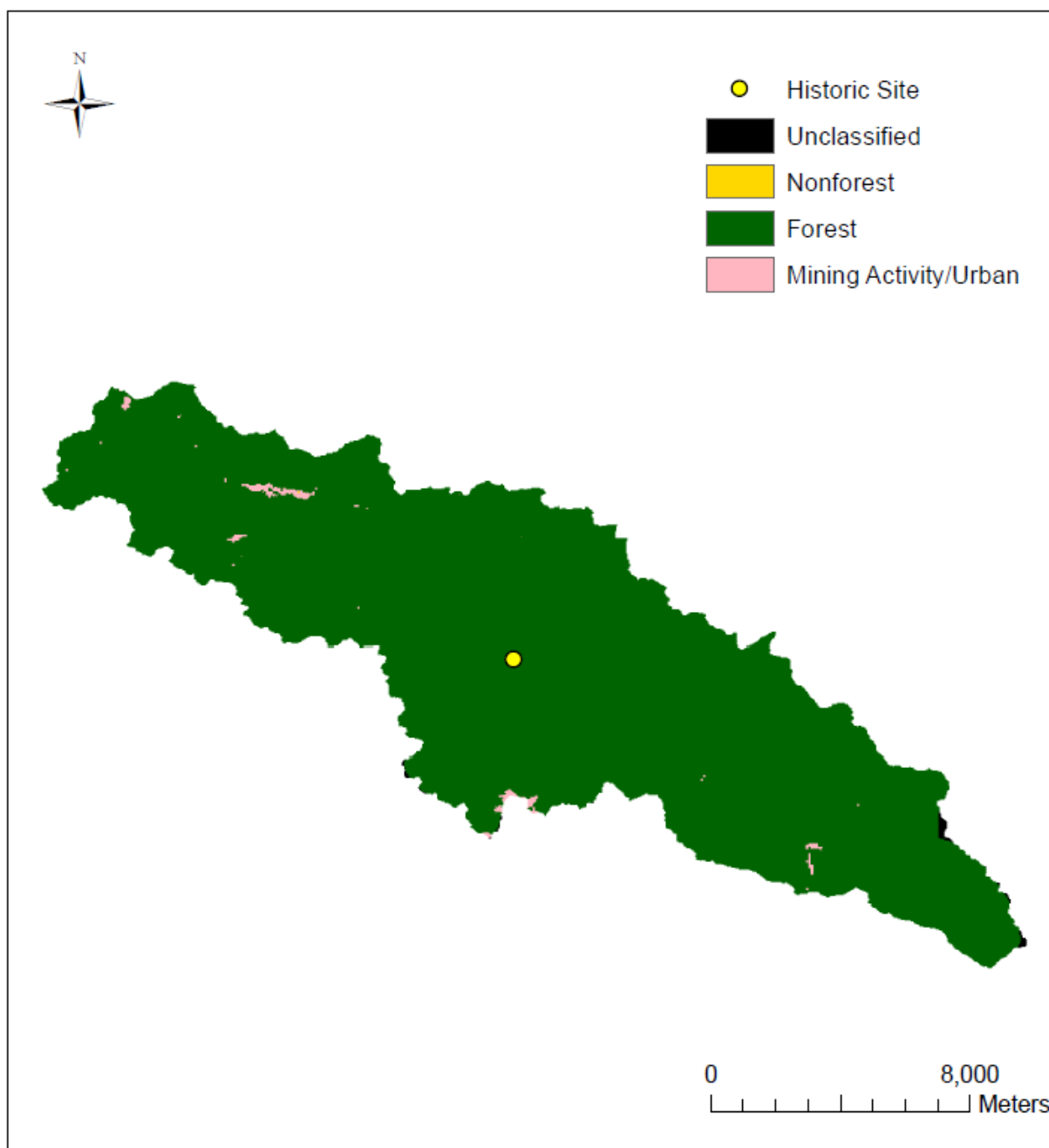


Figure 3.2. Classified image of Pinnacle Creek HUC 12 subwatershed in 1976 with the historic site of *Cambarus veteranus*.

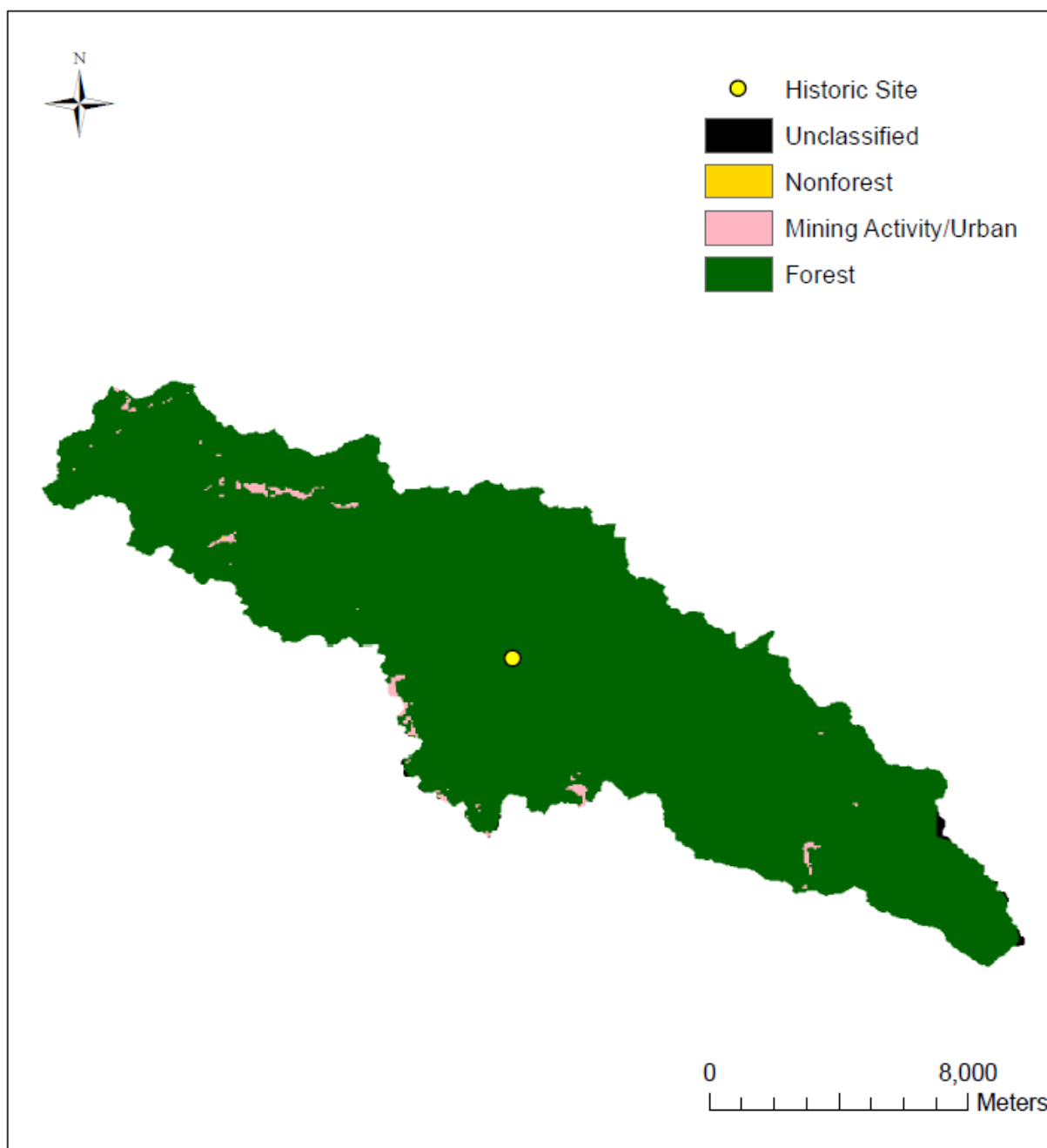


Figure 3.3. Classified image of Pinnacle Creek HUC 12 subwatershed in 1981 with the historic site of *Cambarus veteranus*.

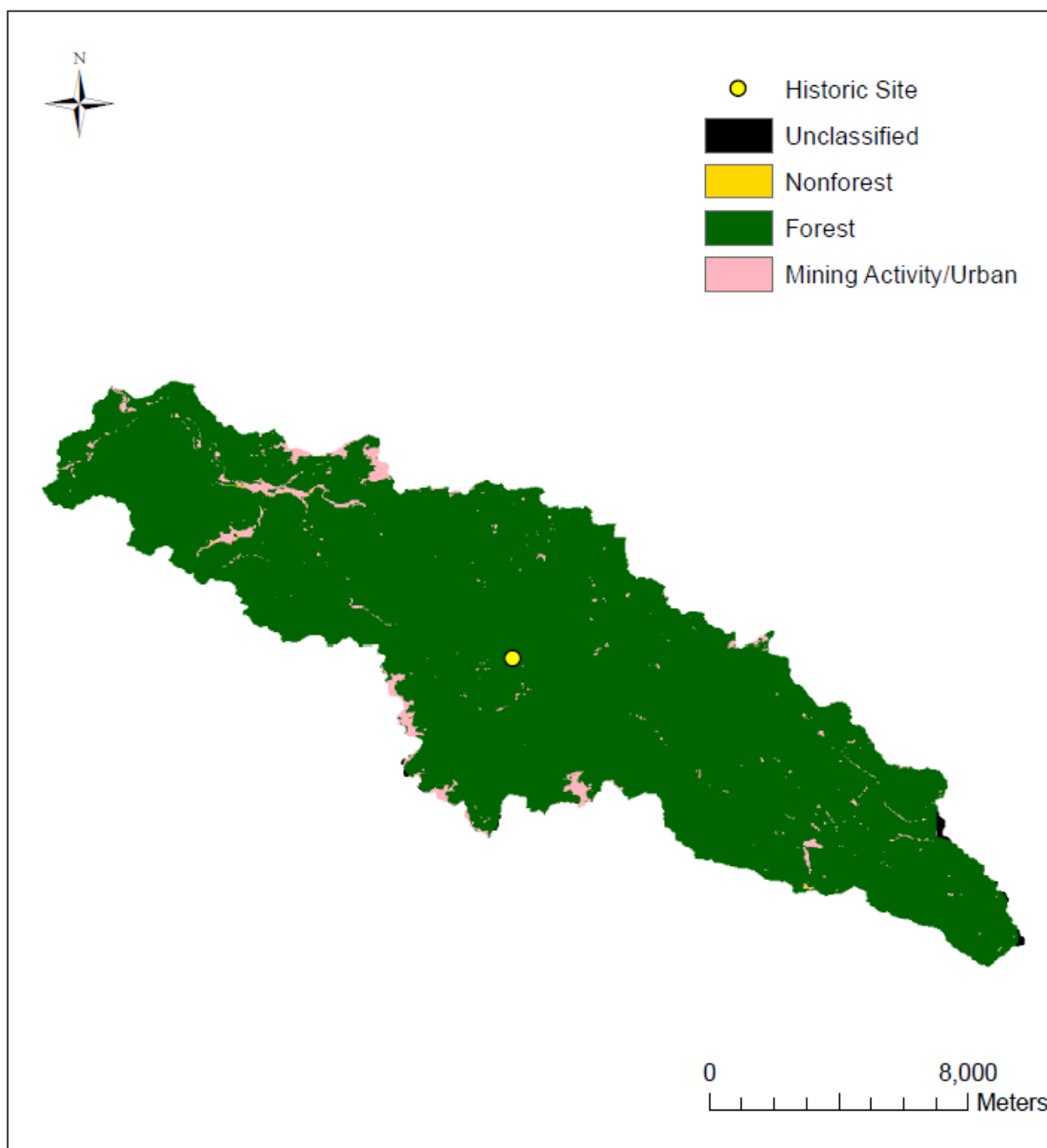


Figure 3.4. Classified image of Pinnacle Creek HUC 12 subwatershed in 1984 with the historic site of *Cambarus veteranus*.

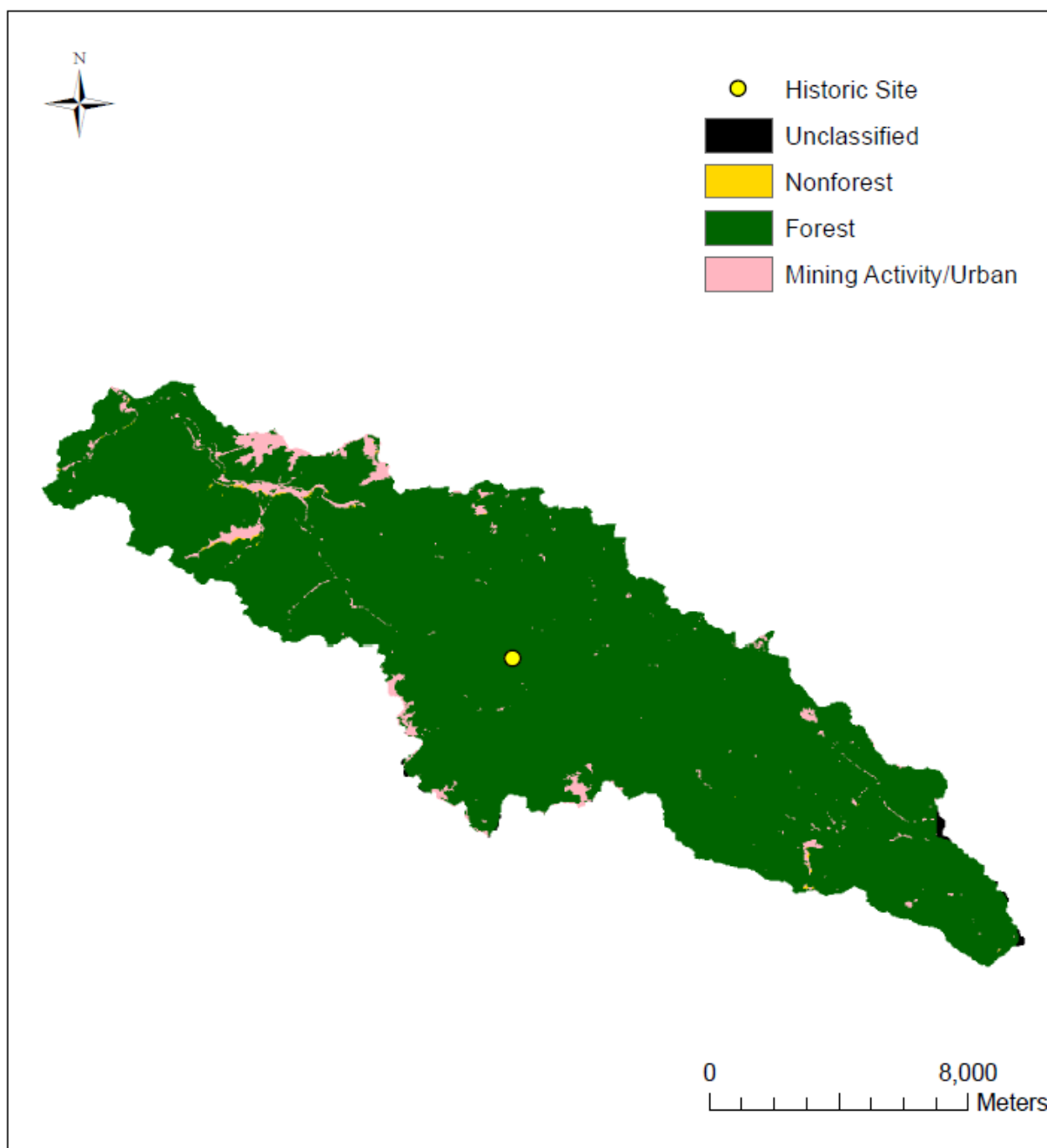


Figure 3.5. Classified image of Pinnacle Creek HUC 12 subwatershed in 1987 with the historic site of *Cambarus veteranus*.

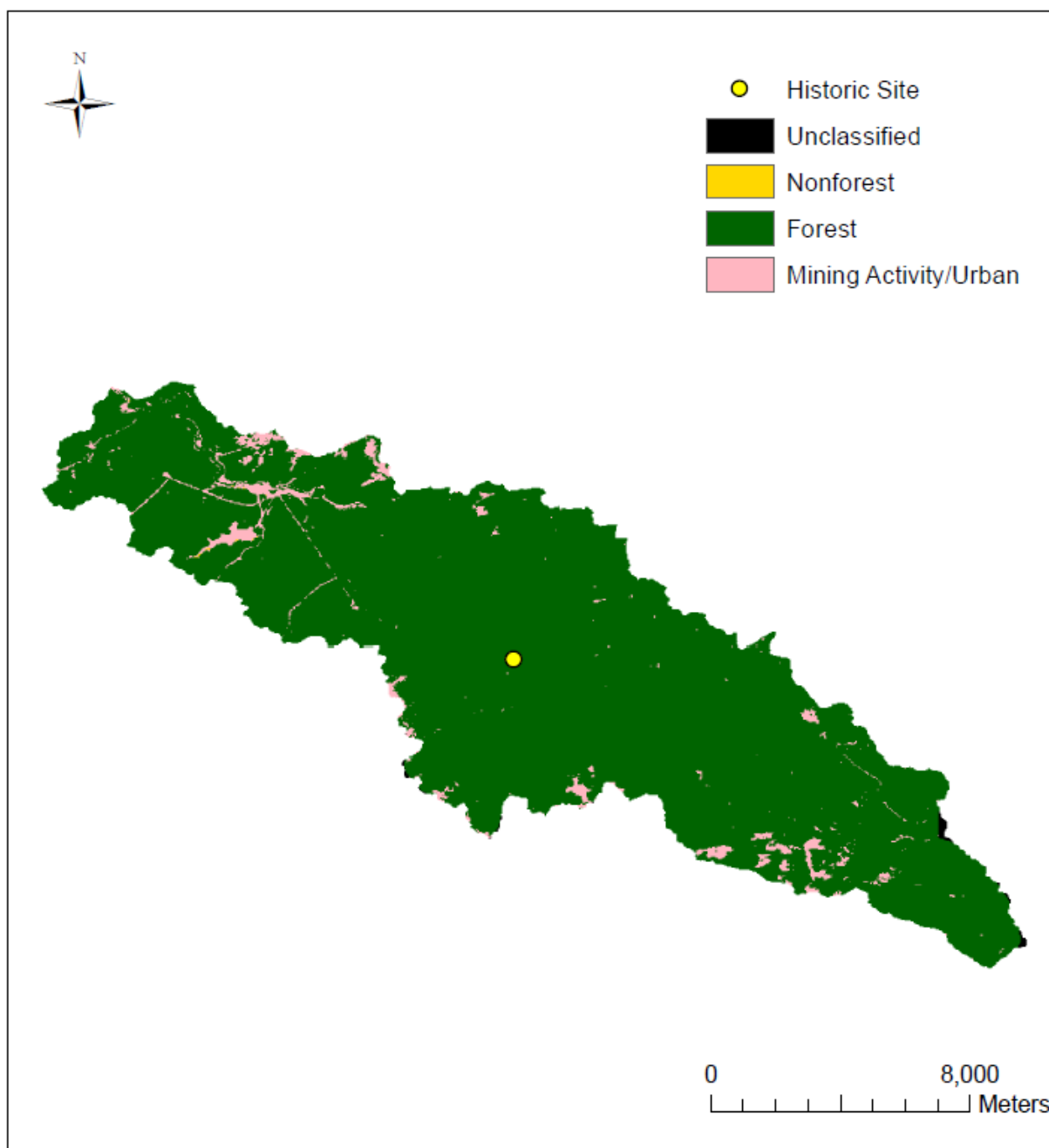


Figure 3.6. Classified image of Pinnacle Creek HUC 12 subwatershed in 1991 with the historic site of *Cambarus veteranus*.

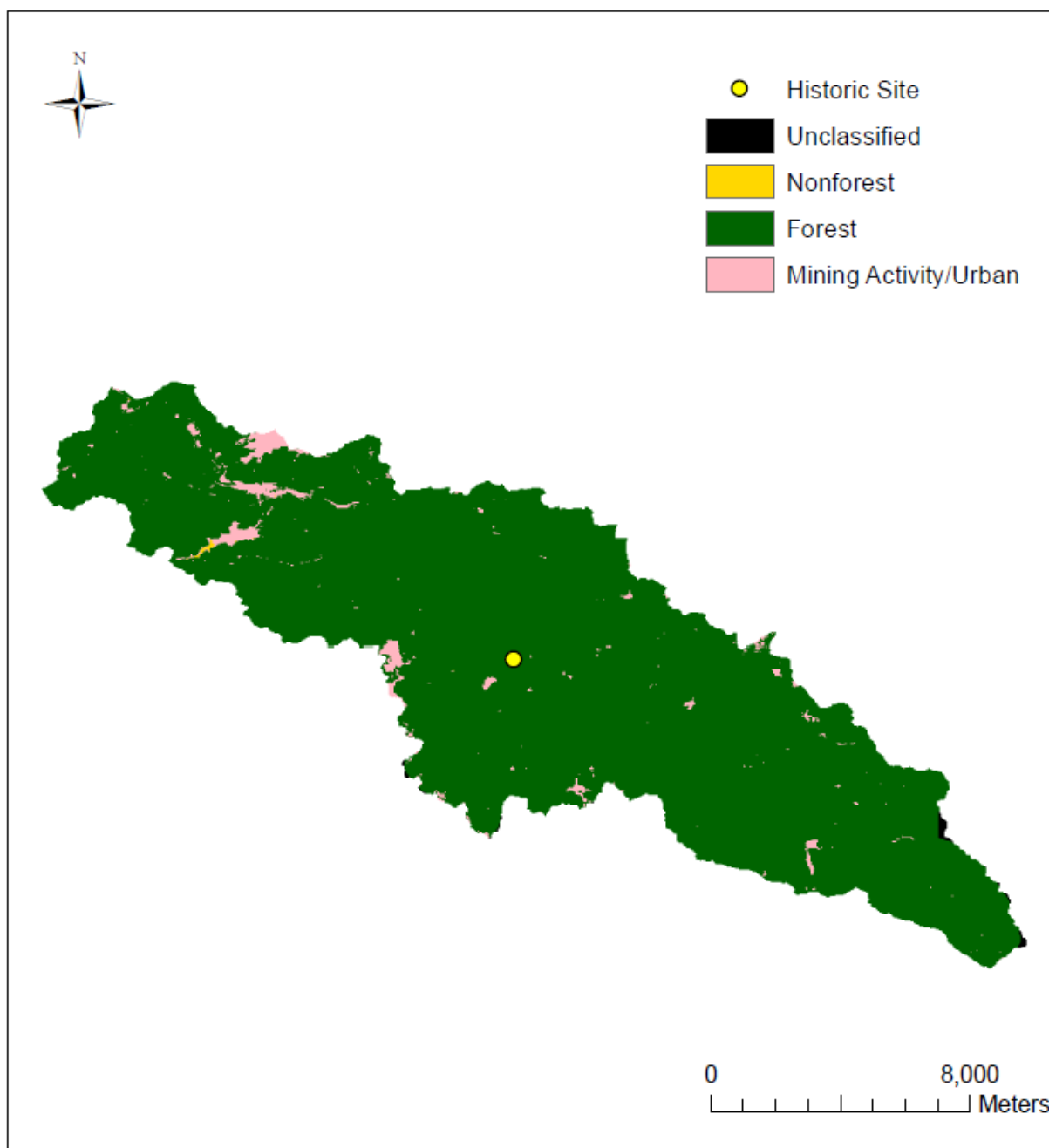


Figure 3.7. Classified image of Pinnacle Creek HUC 12 subwatershed in 1995 with the historic site of *Cambarus veteranus*.

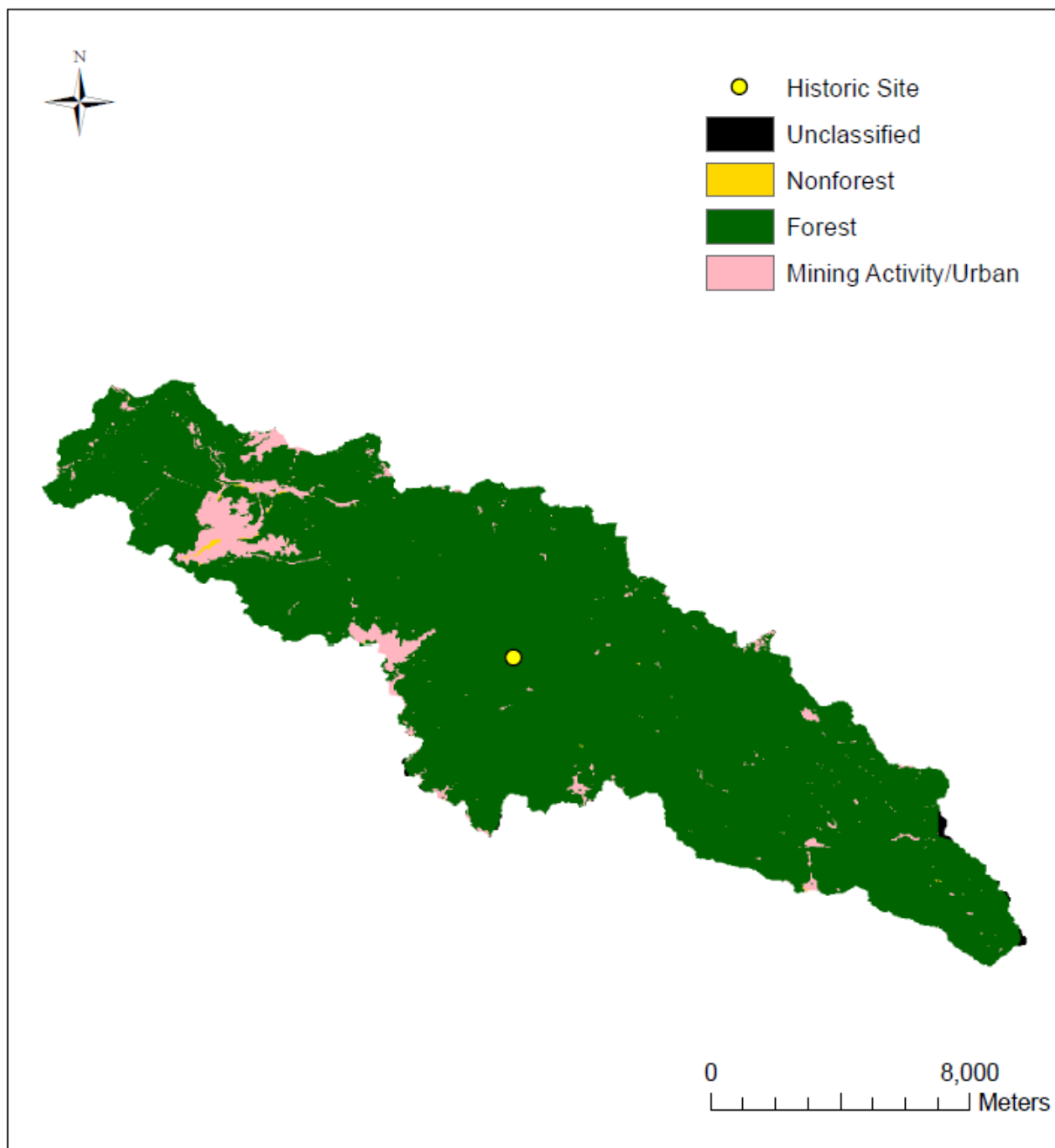


Figure 3.8. Classified image of Pinnacle Creek HUC 12 subwatershed in 1998 with the historic site of *Cambarus veteranus*.

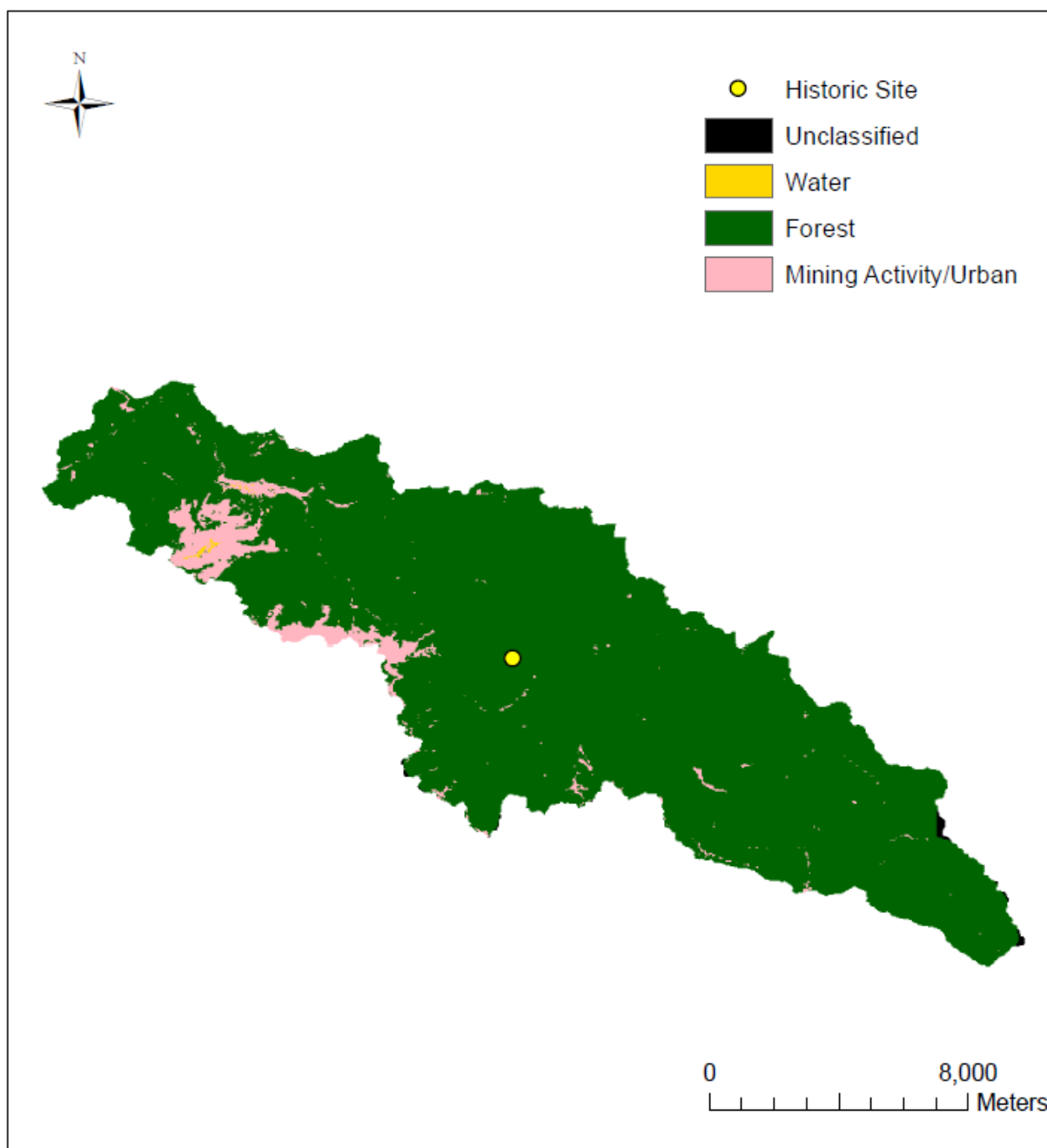


Figure 3.9. Classified image of Pinnacle Creek HUC 12 subwatershed in 2001 with the historic site of *Cambarus veteranus*.

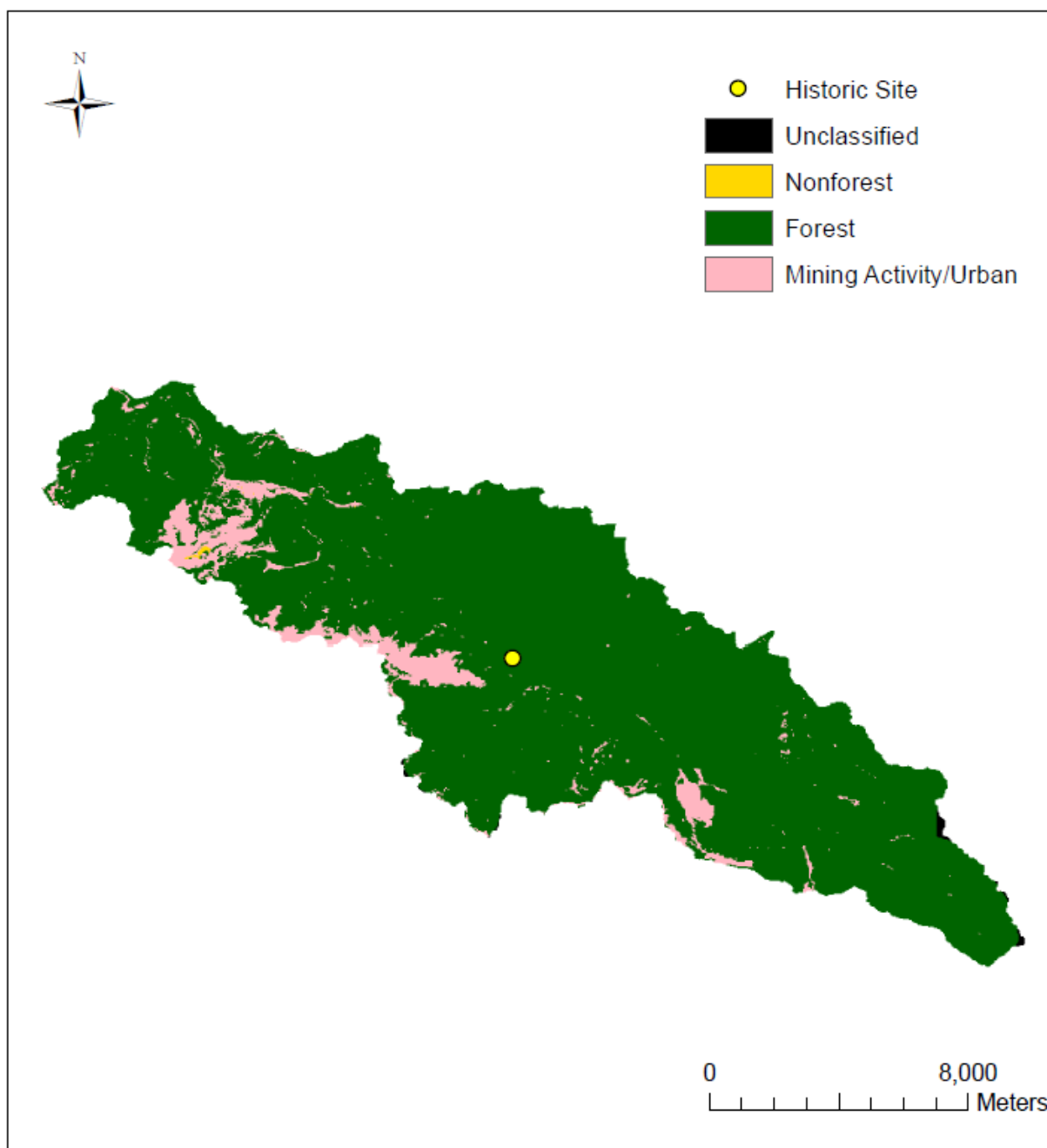


Figure 3.10. Classified image of Pinnacle Creek HUC 12 subwatershed in 2005 with the historic site of *Cambarus veteranus*.

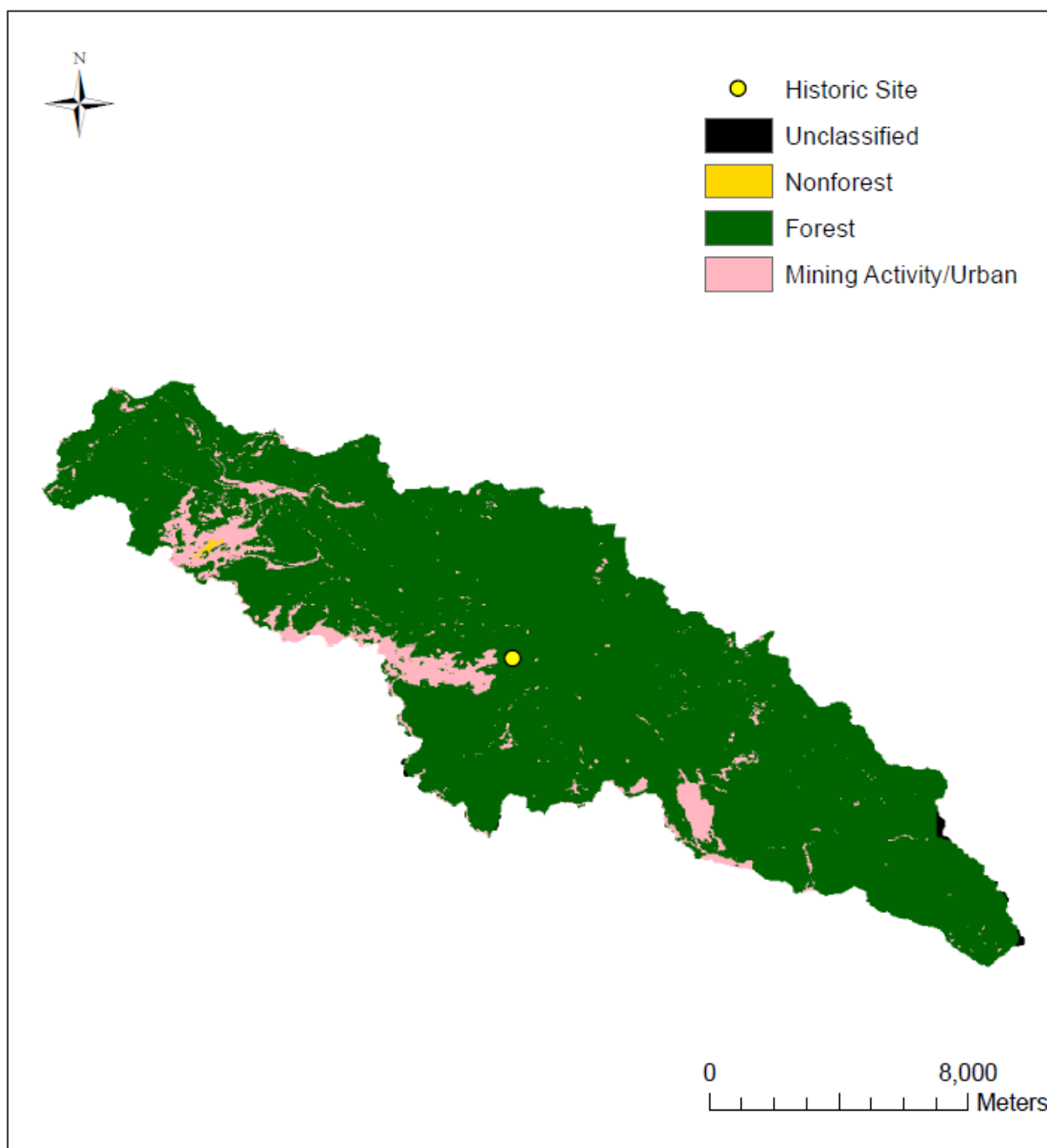


Figure 3.11. Classified image of Pinnacle Creek HUC 12 subwatershed in 2008 with the historic site of *Cambarus veteranus*.

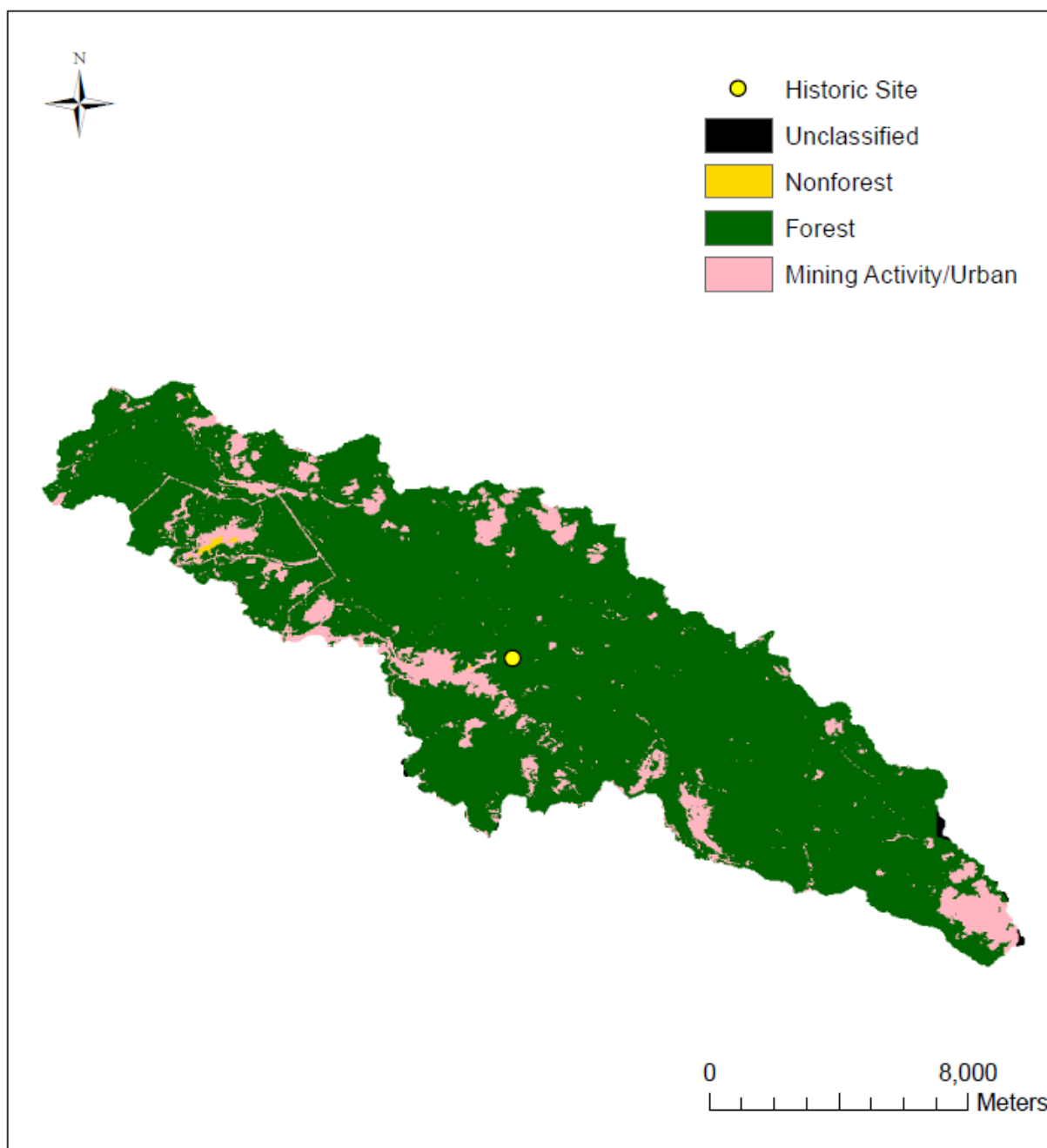


Figure 3.12. Classified image of Pinnacle Creek HUC 12 subwatershed in 2013 with the historic site of *Cambarus veteranus*.

Appendix C: Marshall IRB Approval Letter



Office of Research Integrity

July 27, 2015

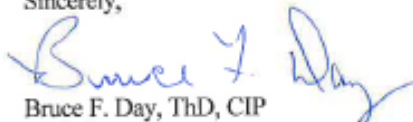
Emma M. Arneson
1907 18th Street
Huntington, WV 25701

Dear Ms. Arneson:

This letter is in response to the submitted thesis abstract titled "Monitoring Land Cover Change in the Historic Range of *Cambarus veteramus* in West Virginia Using a 1973-2013 Landsat Time Series." After assessing the abstract it has been deemed not to be human subject research and therefore exempt from oversight of the Marshall University Institutional Review Board (IRB). The Institutional Animal Care and Use Committee (IACUC) Chair has also deemed this not to be animal research requiring their approval. The information in this study is not considered human subject or animal research as set forth in the definitions contained in the federal regulations. If there are any changes to the abstract you provided then you would need to resubmit that information to the Office of Research Integrity for review and determination.

I appreciate your willingness to submit the abstract for determination. Please feel free to contact the Office of Research Integrity if you have any questions regarding future protocols that may require IRB review.

Sincerely,



Bruce F. Day, ThD, CIP
Director

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