

Chapter 2

Land-Cover Change and Climate Change

Analysis of the Amur River Basin Using Remote Sensing Data

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Abstract We used remote sensing data to clarify recent climate changes and land-cover changes in the Amur River Basin. We also analyzed locations of remarkable land-cover and land-use changes that are of concern for their socioeconomic impacts on fluvial geomorphology. We focused especially on wetlands on the fluvial plain along the Amur River main stem. Land-cover changes in Northeast China are more extensive and rapid than those in Russia and related with land degradation in the north. Rapid land-cover changes have had notable effects on surface erosion and land degradation where is repeated flooding of branches of the Amur River in Northeast China.

Keywords Remote sensing • CRU TS • Amur river • Land-cover change

2.1 Introduction

Local environmental changes originating from rapid land-cover change have been occurring recently in the Amur River Basin. For instance, agricultural development has led to increases in degradation of wetland habitat for migratory birds and fishes, sedimentation of rivers from sloping fields, chemical loading of rivers, and air pollution by forest fires. Biodiversity has decreased in the lower part of the basin. In the Chinese part of the basin, government projects have expanded farming districts. The forest area has been decreased in recent period (Zhang 2000; Ganzey 2005). Cultivated area increased in the 1980s and 1990s, and there are several urban expansion with

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urban sprawl along the Amur River after 1990s in Northeast China (Liu et al. 2001; Luo 2001; Deng et al. 2001; Doi and Zhang 2001; Ganzey 2005; Haruyama 2005; Haruyama et al. 2010; Murooka et al. 2007a), and paddy fields there have become an important Chinese national food production zone in Northeast China (Motoki 2001). The Sanjiang plain is also “grain cradle of China” and there are large grain granaries in this plain. However, the creep and soil erosion are suddenly occurred after torrential rainfall in Sanjiang Plain because of its weak resilience of land cover function.

In contrast, the Russian part of the basin has been in a state of economic depression since the collapse of the Soviet federation. Therefore, regional differences between the Chinese and Russian parts of the Amur Basin are remarkably profound. Today, natural disasters such as basin wide floods, creep and gully on the slope land, surface soil erosion, slope collapse, land degradation, increased sedimentation in the river bed, and rapid changes of river course are strongly affected by this uneven distribution of environmental degradation. The land surface disturbances affected the circulation in the Amur-Okhotsk system by analyzing of Iron distribution in the river water and sea water in the Sea of Okhotsk (Shiraiwa 2005; Himiyama 2001; Murooka et al. 2007b; Yamagata et al. 2007; Haruyama et al. 2014). Haruyama et al. (2013) explained that wetlands in the Amur River flood plain are important flood retarding zones or buffer zones for ephemeral inundation under the torrential rainfall in monsoon summer and calculated the peak cut off volume of the severe flooding in the middle reaches of the Amur River Basin. The principle of spatial deviation should be understood when planning mitigation and conservation activities.

The purposes of our study are to: (1) survey land degradation in the Amur River Basin; (2) climate change clarification using CRU TS; (3) determine zones of especially severe land-cover change during the last 20 years; and (4) evaluate principal influences on land-cover and land-use change in the basin with land degradation. We primarily used remote sensing data, with additional analyses of individual regions. By using the Normalized Difference Vegetation Index (NDVI) to map the area, we were able to pinpoint regions undergoing marked land-cover change and to explore trends of these changes.

2.2 Geographic Setting of Study Area

The Amur River flows westward from its headwaters before turning in a large arc to flow east toward the Sea of Okhotsk. The river is joined by the Ussury River, which flows northward, near Khabarovsk, and by the Songhua River, which flows north-eastward, near the Sanjiang Plain. The Amur separates into several branches near its mouth, such as the Sungari (Songhua), Zeya, Ussury, Shilka, Argun, and Bureya rivers. Mean discharge of the Amur at Khabarovsk observation station was 330 km³/year from 1970 to 1995 (Tachibana 2003). The river surface is usually frozen in winter, and discharge peaks in early spring owing to snowmelt and in summer from heavy rainfall.

Tectonic evolution of the Amur River Basin took place during the Mesozoic and Cenozoic eras. There is Paleozoic Mongol-Okhotsk folding structure in the north

western area of the Amur River Basin with numerous large faults. The southern Amur Basin is situated on the Bureya and Khanka massifs where are fragmented Chinese platform. The eastern Amur Basin is within the Sikhote-Ali folding area (Makhinov 2010). The geomorphology appears to have been stable during the Holocene; however, in recent years, slope erosion and riverbank erosion of the main river course have been common. The western part of the basin is mountainous, reaching more than 1000 m above sea level, and the fluvial plains with altitudes below 100 m are around the Sanjiang Plain. Peat wetlands are in floodplains and valley floors in the hilly country south of the Amur River. The narrow flood plain continues to the mouth of the Amur and there are swampy are after passing though Khabarovsk. In the city of Harbin, the annual mean temperature is 4.6°C, and the mean temperature in January is −20°C and the water surface of the river is frozen in winter (China Map Office 2004). Rainfall concentrates in summer and one crop is planted each year in the basin (Lin and Hasegawa 2005).

Ganzey (2005) explained that the coniferous forest is patched around low mountain ranges, mixed and deciduous forests are mainly located in gentle slope hills and mountain area. The wide grass land and scrubs are in Mongolia territory, however, the above mentioned vegetation has been decreased and changed to agriculture development area.

2.3 Data

2.3.1 Satellite Data

Our remote-sensing dataset was acquired by the Advanced Very High Resolution Radiometer (AVHRR) on the Pathfinder satellite. The Pathfinder AVHRR Land dataset for 1982 through 2000 from the National Aeronautics and Space Administration/Goddard Space Flight Center (NASA/GSFC, <http://daac.gsfc.nasa.gov>) was analyzed for recent land-cover change in the Amur Basin (Fig. 2.1). Climate Research Unit Time Series (CRU TS) Dataset 2.0 that is important data set for analysis of climate change in the Amur River Basin was applied to the temperature and precipitation trends.

The AVHRR sensor measures emitted and reflected radiation in five channels of the electromagnetic spectrum: channel 1 (visible light, 0.58–0.68 μm), channel 2 (near-infrared, 0.725–1.1 μm), channel 3 (mid-infrared, 3.55–3.93 μm), channel 4 (thermal infrared, 10.5–11.5 μm), and channel 5 (thermal infrared, 11.5–12.5 μm). Channel 3 is used for sea surface temperature mapping and is not available in the PAL data. Radiances from channels 4 and 5 depend on surface temperature and can be used to map that temperature on a global basis. This dataset divides the year into 36 seasons of 10 days each. The 10-day composite data from the data removes the effects of clouds by choosing observations on cloud-free days. The Interrupted Goode Homolosine Projection used for this data must be converted to

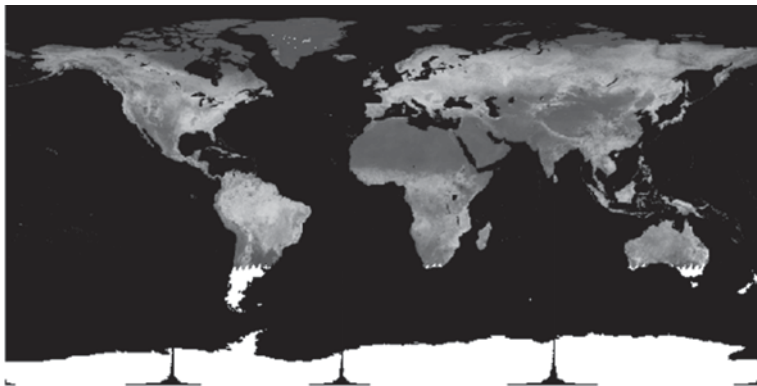


Fig. 2.1 NOAA/AVHRR PAL data. PAL NDVI data converted to equal angular projection from the interrupted goode homolosine projection

an equal-angle projection so that pixel latitudes and longitudes can be determined. Therefore, the spatial resolution was converted from 8 km to 0.1° (about 10 km on the map) of both latitude and longitude, using a tool provided by NASA/GSFC.

AVHRR channel 1 is a part of the spectrum in which leaf chlorophyll absorbs incoming radiation, and channel 2 is a region in which spongy mesophyll leaf structure generates considerable reflectance. These two channels can therefore be used to derive information on vegetative land cover via the NDVI. The NDVI value, which is related to the density and active growth of green vegetation, is calculated from differences in spectral reflection of chlorophyll in the visible light and near-infrared ranges (Myneni et al. 1997; Kondoh et al. 2005; Nemani et al. 2003). The NDVI has been shown to be strongly correlated with vegetation parameters such as land cover and land use (Sannier et al. 1998), green leaf area index (LAI) (Spanner et al. 1990), and green-leaf biomass (Box et al. 1989), and is of considerable value for vegetation discrimination. Myneni (1995) provided a theoretical interpretation between LAI and vegetation. Wang et al. (2005) suggested that NDVI-LAI relationship can vary both seasonally and inter annual in tune with variations in phenological development of the trees and in response to temporal variations of environment. Tucker (1979) suggested the different spectral vegetation indices derived from remote sensing NDVI has been the widely used. The NDVI is the most widely used vegetation index, and is calculated from PAL data by

$$NDVI = \frac{Ch.2 - Ch.1}{Ch.2 + Ch.1}$$

The NDVI equation produces values between 1.0 and -1.0 , where positive values indicate green vegetation and negative ones non-vegetated surfaces such as water, barren land, ice, and snow.

Fig. 2.2 Salt marsh; surrounding area converted to corn fields and industrial zones



Fig. 2.3 Harbin (urban expansion) with the Songhua river

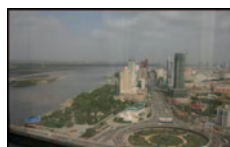
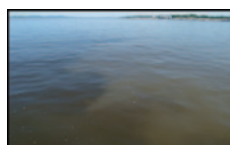


Fig. 2.4 Wetlands and paddy field



Fig. 2.5 Water surface of Amur and Songhua rivers (turbid water is the Songhua river)



2.3.2 Land-Use Pattern Corroboration of Remote Sensing Data

The amount of agricultural land in Northeast China that in remote sensing data was irrigated between 1980s and 2000s, was determined from the Heilongjiang Province Statistical Yearbook (2001). The area sown with four main commercial crops such as rice, wheat, corn, and soybeans, between 1978 and 2000, along with patterns of production transition for remote sensing data, were determined using the other local-level statistical materials. The Sanjiang Plain is important signal of recent land use change (China Statistics Office 2001; Haruyama 2005; Haruyama et al. 2010, 2014). The sizes of paddy and upland crop fields in the province were determined by questionnaires administered by local officials. The social background of agriculture development with surface water and underground water utilities was surveyed and we conducted questionnaire survey how is affected by the agriculture engineering adaptation in the Heilongjiang Province. We organized field investigations in which we used GPS system to record land cover factor on the Sanjiang Plain, Songnen Plain, and around Khabarovsk Krai in 2002–2006 (Figs. 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, and 2.9).

Fig. 2.6 Cornfields (artificial slope land around hillside)



Fig. 2.7 Paddy fields with irrigation and drainage in the three-river plain



Fig. 2.8 Soybean fields and soil erosion around hillside



Examples of field observation photos from numbered locations are given in Figs. 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, and 2.9. Figure 2.2 shows a typical salt marsh where the surrounding area was being converted to corn fields and industrial zones. Figure 2.3 of Harbin city area shows urban sprawl and development with rapid building construction, as is common in this region. The river is flying river bed after construction of embankment. Figure 2.4 shows a typical wetland landscape, one of several types of wetlands that are being converted to farmland in the Harbin urban expansion area. Figure 2.5 shows sediment in river water at the confluence of the Amur and Songhua river basins, which originates from agricultural development and slope erosion in Northeast China. Figure 2.6 shows a typical cornfield landscape on Sanjiang Plain in which the original forest is almost gone. Figure 2.7 shows rice fields on the floodplain, with irrigation and drainage channels. Figure 2.8 shows soybean fields on old ruggedness mountain and hill escarpment area in Northeast China. We used these photographs of the landscape and land-use conditions as 254 ground truth points during our analysis of remote sensing data.

Local environmental change is affected by global long-term climate change and strongly by recent human activities as short-period environmental change. The rapid agriculture development of flood plain and hill slopes with cutting forest are both factors for soil erosion and creep of the hill slope. To quantify recent climatic changes in our study area, we analyzed portions of the Climate Research Unit (CRU) time series (TS) dataset 2.0. The CRU TS data are supplied on a 0.5—degree grid covering the global land surface. The dataset provides monthly data on cloud cover, diurnal temperature range, precipitation, temperature, and vapor pressure for the period 1992–2000. For our purposes, long term precipitation and temperature

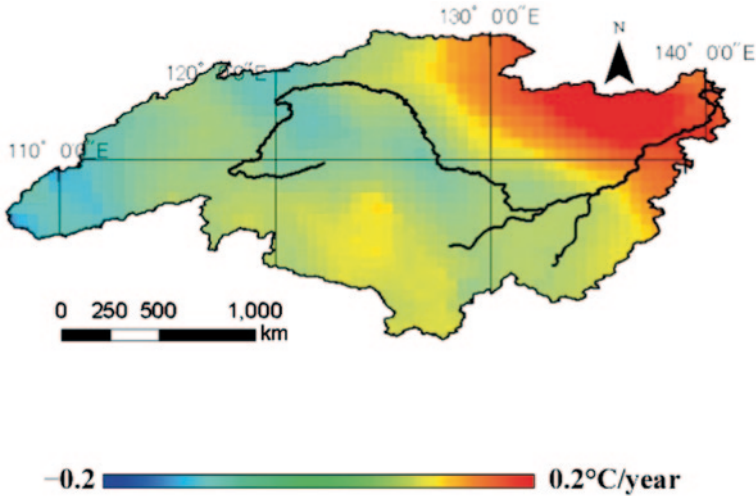


Fig. 2.9 Secular trend of mean temperature in January using CRU TS from 1982 to 2000

data are the most useful of these. We analyzed mean monthly temperatures between 1981 and 2000, annual mean temperatures between 1961 and 2000, monthly precipitation between 1982 and 2000, and yearly precipitation between 1961 and 2000 to detect and characterize long-term climatic changes related to land-cover change issues.

2.4 Land-Cover Change Analysis

Kondoh (2004) analyzed river basin-scale vegetation change and land-cover changes from 1982 to 2000 in the PAL dataset and we derived land-cover change trend over the entire Amur River Basin using this method. Haruyama et al. (2014) explained that the result of each NDVI factor of continuous land cover change in last 20 years. After that, we reanalyzed the same data with CRU TS used the following four quantities: the sum of NDVI (ΣNDVI) during the year, maximum NDVI ($\text{NDVI}_{\max}$), standard deviation of ΣNDVI (NDVI_{std}), and the trajectory of the surface temperature—NDVI scatter chart (TRJ) (Nemani and Running 1997; Price 1984; Haruyama et al. 2014). $\text{NDVI}_{\max}$ is a widely used for analysis of vegetation activities and reliable index related to maximum leaf area index (LAI) or maximum biomass. LAI is an important biophysical influencing land cover processes (Bonan 1993). We extracted the maximum NDVI for each year and examined its trend during our 19-year analysis period. ΣNDVI is an index that corresponds to annual biomass, as confirmed by Goward et al. (1985) and Box et al. (1989). ΣNDVI was calculated by

$$\sum NDVI = \sum_{i=1}^N a_i,$$

where a_i is the NDVI value of a (10-day) season and N is the number of seasons (36). The threshold between vegetated and non-vegetated land is commonly chosen at $NDVI=0.1$. Pixels with NDVI less than 0.1 were excluded from our calculations.

We selected $NDVI_{std}$ as an index of vegetation disturbance, because it indicates the biomass increase and decrease in a year owing to forest fires, floods, and similar events. The standard deviation of $\Sigma NDVI$ was also derived for these years in our study period. The $NDVI_{std}$ was calculated by the following:

$$NDVI_{std} = \sqrt{V_x} \quad V_x = \frac{1}{19} \sum_{i=1982}^{2000} (x_i - \bar{x})^2 \quad \bar{x} = \frac{1}{19} \sum_{i=1982}^{2000} x_i$$

x_i is the value of $\Sigma NDVI$ from 1982 to 2000 and V_x is its variance. For instance, both $\Sigma NDVI$ and $NDVI_{std}$ vary throughout the year in regions where floods and forest fires are frequent, as well as in regions where the timing of snowmelt strongly affects vegetation growth.

The TRJ index, which shows the direction of land-cover change, differs with vegetation type (Nemani and Running 1997). For example, TRJ is positive when land cover changes from meadow to bare ground or barren land, and it declines when meadow changes to forest. TRJ is obtained from the scatter chart of surface temperature (Ts) and NDVI, with NDVI on the horizontal axis and Ts on the vertical. Ts is calculated by

$$Ts = Ch.4 + 3.3 \times (Ch.4 - Ch.5)$$

With two channels of thermal infrared data (4 and 5), the split window method of Price (1984) was used to calculate Ts. Therefore, the atmospheric influence was almost entirely corrected. Ts values lower than -100°C were treated as error pixels and assigned error number zero.

TRJ is derived by calculating the inclination of the recurrence straight line after NDVI, and Ts data of 36 seasons are plotted. TRJ was calculated by

$$TRJ = \frac{\sum_{i=1}^N (a_i - \bar{a})(b_i - \bar{b})}{\sum_{i=1}^N (a_i - \bar{a})^2} \quad \bar{a} = \frac{1}{N} \sum_{i=1}^N a_i \quad \bar{b} = \frac{1}{N} \sum_{i=1}^N b_i,$$

where b_i is the Ts value of a season. If NDVI is less than 0.1 and Ts less than -100°C , the pixels are excluded.

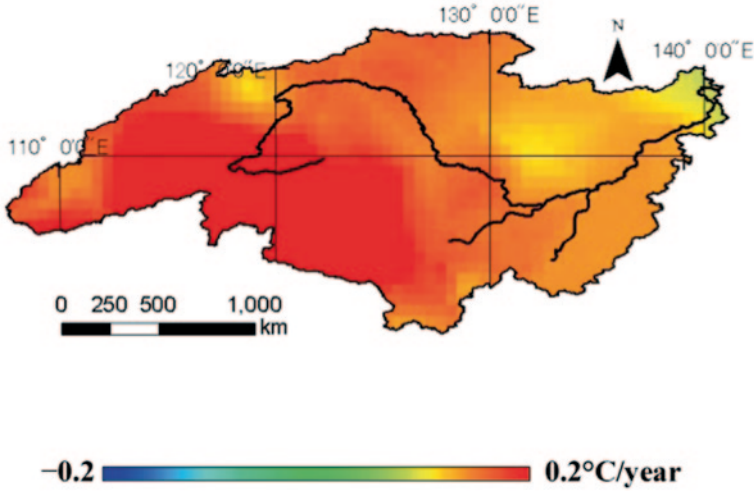


Fig. 2.10 Secular trend of mean temperature in February using CRU TS from 1982 to 2000

Land-cover change can be calculated by applying a straight line to the tracks for every year and analyzing the change of line inclination over the 19-year period. Trends of each parameter (TRJ, Σ NDVI, and $\text{NDVI}_{\max}$) were calculated via

$$\text{Trend} = \frac{\sum_{j=1982}^{2000} (c_j - \bar{c})(d_j - \bar{d})}{\sum_{j=1982}^{2000} (c_j - \bar{c})^2} \quad \bar{c} = \frac{1}{19} \sum_{j=1982}^{2000} (j - 1982) \quad \bar{d} = \frac{1}{19} \sum_{j=1982}^{2000} d_j$$

where, j is the value of a given year and d_j is substituted with each parameter (TRJ, Σ NDVI, and $\text{NDVI}_{\max}$).

Validity of this data results was verified by statistical material analysis and ground truth data from our field investigation; thus, areas with the greatest artificial land alteration were determined.

2.5 Results and Discussion

2.5.1 Climate Research Unit Time Series (CRU TS) Dataset 2.0 Analysis

Figures 2.9, 2.10, 2.11, 2.12, 2.13, 2.14, 2.15, 2.16, 2.17, 2.18, 2.19, and 2.20 shows the secular trend of mean temperature between 1982 and 2000 for the 12 calendar

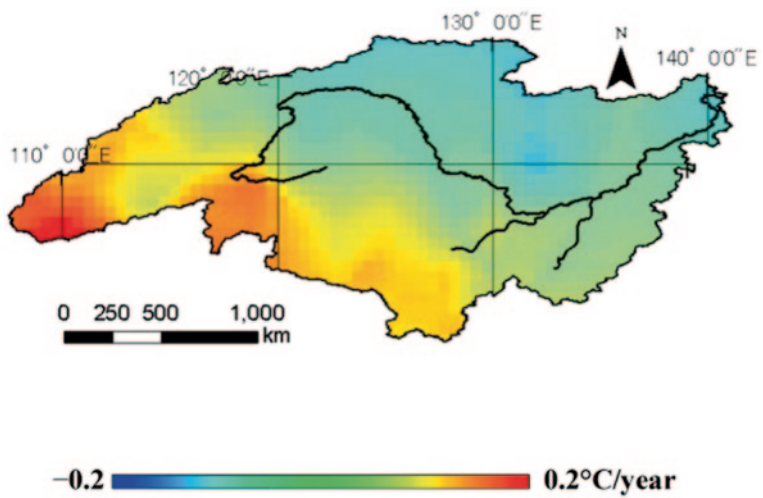


Fig. 2.11 Secular trend of mean temperature in March using CRU TS from 1982 to 2000

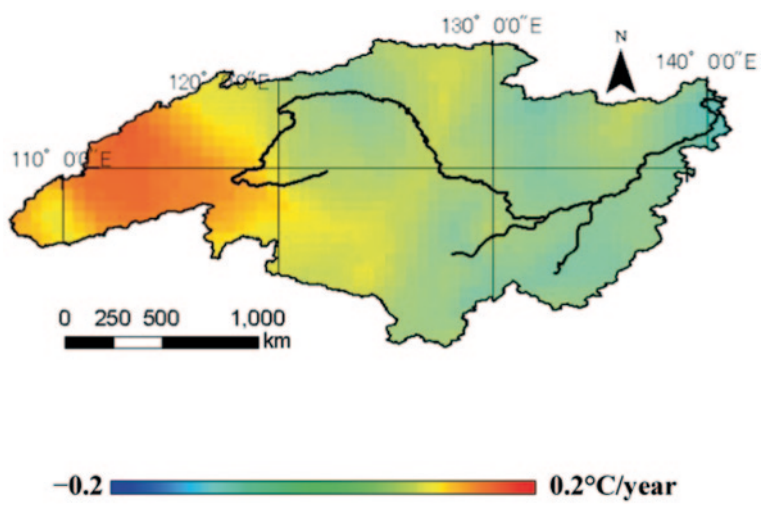


Fig. 2.12 Secular trend of mean temperature in April using CRU TS from 1982 to 2000

months. Figures 2.21 and 2.22 shows the trend of annual mean temperature for two periods, 1961–1990 and 1982–2000 respectively, after trend analysis using the data of CRU TS 2.0 dataset. Our results show that annual mean temperature rose by 0.05 °C/year from 1961 to 1990 and by 0.07 °C/year between 1982 and 2000, especially in the southwest part of the Amur River Basin (Figs. 2.9, 2.10, 2.11, 2.12, 2.13, 2.14, 2.15, 2.16, 2.17, 2.18, 2.19, 2.20, 2.21, 2.22, and 2.23). Mean tem-

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