DETECTION OF CHANGES IN LAND DEGRADATION IN NORTHEAST CHINA FROM LANDSAT TM AND ASTER DATA

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ABSTRACT:

This study aims to determine the accuracy level at which different forms of land degradation can be mapped from medium-resolution satellite data, and to assess how accurately degraded land can be detected from multi-temporal satellite images. Land degradation in the form of salinization and waterlogging in Tongyu County, western Jilin Province of Northeast China was mapped from Landsat TM and ASTER images at 30 m using supervised classification, together with several other land covers. These land covers have been mapped at an overall accuracy of 80% from the TM image with the accuracy for individual covers ranging from 75% to 100% except settled areas. At 80.0%, the accuracy for barren land is higher than that for degraded farmland. The overall classification accuracy was achieved at 75.3% from the ASTER data. The accuracy for degraded farmland rose marginally to 76.7%. It is concluded that moderately degraded land can be mapped from both ASTER and TM data at over 75%. Severely degraded land can be mapped more accurately over 80%. Between 1989 and 2004 grassland decreased from 282.9 km² to 79.8 km² while healthy farmland increased by well over 120%. On the other hand, fallow land increased by 125.2% due to excessively high soil salinity. Besides, degraded farmland and barren land rose by 19.1% and 33.1%, respectively. Thus, inappropriate land reclamation and cultivation are blamed for soil degradation inside the study area.

1. INTRODUCTION

As one of the most common and serious environmental problems in the world, land degradation has affected two billion hectares (22.5%) of agricultural land, pasture, forest and woodland around the world (Oldeman *et al*. 1990). Around 5 to 10 million hectares of agricultural land are lost to degradation annually. Globally, land degradation causes a loss of productivity in drylands valued between US$13-28 billion a year (Yadav and Scherr 1995). It is thus very important to determine the nature, spatial extent, magnitude, distribution, and temporal behaviour of degraded land in order to come up with effective prevention and rehabilitation measures.

Due to its extensive distribution, land degradation is ideally monitored by means of remote sensing. For instance, information on vegetation cover, rain use efficiency, surface run-off and soil erosion can be derived from remotely sensed data. The combined use of such information highlights areas highly susceptible to degradation (Symeonakis and Drake, 2004). Through monitoring changes in grassland biomass production and reclamation activities, Runnstrom (2003) detected the nature and scale of land degradation in the Mu Us Sandy Land of north central China. It is also possible to study land salinization and waterlogging from remote sensing data. Space borne satellite data have shown the potential in deriving information on the nature and spatial distribution of variously degraded lands, such as salinization and waterlogging (Dwivedi, 1994). Areas affected by degradation can be identified and mapped from Landsat Thematic Mapper (TM) images (Raina *et al*., 1993). Information on the spatial extent and distribution of salt-affected soils can be derived from Landsat multispectral scanner (MSS) data. Visual interpretation of Landsat MSS and TM images, in conjunction with ancillary information and adequate ground data, ascertained the extent and spatial distribution of salt-affected soils, water-logged areas and eroded lands (Sujatha *et al*., 2000). Waterlogged areas can also be mapped from a 1:50,000 Landsat TM false-colour composite print. Waterlogged areas and salt-affected soils were delineated from Indian Remote Sensing Satellite (IRS)-1B Linear Imaging Self-scanning Sensor (LISS-I) and Landsat TM data via visual interpretation (Dwivedi *et al*., 1999).

Long-term monitoring of changes in land degradation is usually accomplished by spatially comparing multi-temporal satellite images, a technique known as change detection. It involves looking for differences between two surface models that are obtained at different times. A number of change detection techniques have been devised for this purpose, such as transparency compositing, image differencing, post-classification comparison, band ratioing, and principal components analysis (Mouat *et al*., 1993). Although image differencing and image ratioing are relatively easy to implement, these change analysis methods based on raw pixel values require selection of an appropriate set of thresholds for measuring change. These thresholds are empirically derived to differentiate changes from background variations, which is rather challenging in some cases. By comparison, post-classification change detection allows identification and mapping of amount, location and nature of differences in land covers (Rubec and Thie, 1980). Land-cover change maps derived from post-classification comparison yielded information on the spatial distribution and type of land-cover changes (Phinn and Stanford, 2001). Furthermore, post-classification comparison is the most accurate among image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison (Mas, 1999). However, it is unknown how accurate changes detected from post-classification can be.