REMOTE SENSING OF INSECT PESTS IN LARCH FOREST BASED ON PHYSICAL MODEL

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ABSTRACT

A physical decision method was proposed here to monitor Larch forest insect pests at early stage. Three remote sensing indicators were defined, which are CWC (canopy water content), TVDI (Temperature/Vegetation Dryness Index) and LAI (Leaf Area Index). The Five-scale model and artificial neural network (ANN) were combined to inverse the three factors from Landsat data. Based on training samples of health or attacked pixels, a decision tree was built to classify pest-infected pixels. Field validation showed that the prediction of forest compartments with insect pest were highly consistent with the ground field data.

Index Terms—Insect pest, early monitoring, remote sensing, Larch forest

1. INTRODUCTION

In recent decades, great efforts have been made on remote monitoring model of the forest pest. Lacking of enough mechanism, lots of models were established by statistical regression analysis based on plot data [1-2], which were often constricted in specific areas. Hence, it is necessary to develop more general models. Besides, most studies focused on the stage when the leaves change color or shatter. Thus, two physiological characteristics, defoliation and the change of leaf color, were often used to monitor forest compartments with insect pest were highly consistent with the ground field data. A physical decision method was proposed here to monitor Larch forest insect pests at early stage. Three remote sensing indicators were defined, which are CWC (canopy water content), TVDI (Temperature/Vegetation Dryness Index) and LAI (Leaf Area Index). The Five-scale model and artificial neural network (ANN) were combined to inverse the three factors from Landsat data. Based on training samples of health or attacked pixels, a decision tree was built to classify pest-infected pixels. Field validation showed that the prediction of forest compartments with insect pest were highly consistent with the ground field data.

1. INTRODUCTION

In recent decades, great efforts have been made on remote monitoring model of the forest pest. Lacking of enough mechanism, lots of models were established by statistical regression analysis based on plot data [1-2], which were often constricted in specific areas. Hence, it is necessary to develop more general models. Besides, most studies focused on the stage when the leaves change color or shatter. Thus, two physiological characteristics, defoliation and the change of leaf color, were often used to monitor forest health status after trees being attacked. Suitable for loss assessment, however, they are not so good to detect the insect pests at earlier stage. It’s usually at the middle or late stage of insects attacking when the physiological changes are detectable by remote sensing data. If possible, early stage monitoring will be more useful to help save the affected trees. Moreover, VIS and NIR data were widely applied in the pest monitoring research; however, there are rare cases on the application of TIR data.

The objective of this paper is to combine the theories of ecology, forest protection and quantitative remote sensing to monitor forest insect pests, including bores and leaf-eating insects. The Five-scale forest physical model [3] and artificial neural network (ANN) were combined to inverse forest pest information from Landsat data.

2. INDICATOR SELECTION

This section presents a selection solution to detect both leaf-eating pest and borers. LAI can be used to calculate defoliation, which is an important visual feature to detect tree damage by leaf-feeding insects. Chlorophyll is another important forest pest indicative factor to reflect the leaf color change [4]. Besides LAI and chlorophyll, what other parameters can be used to improve monitoring accuracy?

There is a wide range of forest pests. Based on location and different ways of pest feeding, forest pests can be usually divided into four categories, namely, root pests, sucking type insects, leaf-eating insects and borer. However, all types of pests would make trees lose water. Field survey shows that the damage degree of larch forest was significantly correlated with the water content of the needles. For example, Fig. 1 shows the xylem of a weak larch and a severely damaged trunk, which confirms that the water conduction tissue has been severely damaged. Thus, the vegetation water status might be another critical parameter, to reflect plant reaction on pests. In fact, foliage water content has already been found as an indicative factor to monitor beetle based on previous studies [5-6]. Therefore, timely and accurate monitoring or diagnosis of leaf or canopy water content may reflect the physiological status of the forest, which can be an important indicator of the disaster warning [7].

![Fig.1 the photos of different larch xylem: (a) healthy trunk (b) weak trunk (c) severely affected trunk](image)

Of course, drought can also lead to low canopy moisture, which should be identified before. Therefore, it is necessary to simultaneously retrieve canopy moisture and soil moisture and help identify the occurrence of forest pests in the early stage from remote sensing data. In fact, the CWC (canopy water content) and EWT (equivalent water content) are often used to represent the stand level and leaf level of...
water content respectively; while, TVDI is highly correlated with soil water content. Thus, this paper will use three indicators from remote sensing, including TVDI [8], CWC and LAI, to relate them with forest pests.

To evaluate the feasibility of CWC inversion from the Landsat data, the sensitivity of the reflectance characteristics of coniferous needles on EWT was studied based on the filed data and the LIBERTY (Leaf Incorporating Biochemistry Exhibiting Reflectance and Transmittance Yields) model. The results show that three spectral indices, which are MSI (Moisture Stress Index), NDWI (Normal Difference Water Index) and GVMI (Global Vegetation Moisture Index), were highly correlated with EWT. Especially, GVMI is not sensitive to whether the needle is clustered or not. GVMI uses two broad bands (NIR and SWIR), which can be calculated from Landsat TM/ETM+ data. Therefore, it is confirmed that Landsat TM/ETM+ data is able to inverse the forest CWC, which lays a solid theoretical foundation for the following research. Then, the inversion research on the three indicative factors was performed using both VNIR and TIR data, combined with physical-based Five-scale model [3] and ANN.

3. DATA

3.1. Ground data

Ground data includes basic data and field survey data. Basic data were collected from both local and State Forestry Administration sectors, including (1) topographic map data and forest map with scale of 1:50 000; (2) Basic statistics data including the sub-compartment materials, forest pests occurrences from historical survey of forest resources; (3) Digital Elevation Model (DEM) using SRTM data [9].

Field surveys include:

(1) Sample plots: A representative forest farm, YIERSHI in Aershan Mountain in Inner Mongolia, China, was selected as our research base. 17 plots (30m×30m) were established according to different combinations of forest health status and forest age. For each plot, the following parameters were recorded, including plot location, forest pest conditions, tree densities, canopy density and defoliation. Meanwhile, the forest structure of each plot was also been measured, including tree height ($H$), trunk high ($H_a$), canopy height ($H_c$) and the canopy radius ($R_c$). The data was mainly used as prior knowledge for Five-Scale model to inverse LAI or CWC from remote sensing data. Thirty groups of forest structure data were measured and used to fit the relationship between DBH and the other parameters, which can be found in (1):

$$
H = 2.4972 \times DBH^{0.399} \quad (R^2 = 0.88)
$$

$$
H_a = 0.4916 \times DBH^{0.089} \quad (R^2 = 0.51)
$$

$$
H_c = H - H_a
$$

$$
R_c = 20.374 \times DBH + 87.717 \quad (R^2 = 0.733)
$$

(2) Simultaneous satellite-ground observations: August 19, 2008 was the overpass day for Landsat satellite, thus selected as the simultaneous ground observation date. The compartment 61 was the observed forest stand. During the overpass time, the canopy spectral and radiative temperatures were measured by Handheld ASD spectrometer (0.38-1.1$\mu m$) and Infrared thermometer (8-14$\mu m$). Crown structure parameters, EWT and chlorophyll content were also measured. LAI was measured by WinSCANOPY for Canopy Analysis (Regent Instruments). Measurements show that the weight water content of healthy coniferous needle was between 60.32% and 64.56% with an average value of 62.09%. The average EWT of healthy needles equaled 100.98 g/m$^2$. The averaged total chlorophyll content was 1.8mg/g, which was equivalent to 315 mg/m$^2$. The above data were used to calibrate parameters of Five-Scale model and some part was used for evaluation.

(3) Contrast observation: Temperature-related controlled trial was done for four kinds of needle clusters with different chlorophyll content (green or yellow leaves) and different water content (half-green dry or wet leaves). Figure 2 shows that, in the same environmental conditions, the radiative temperature changes of the four kinds of needles are very regular. Yellow leaves were always warmer than green leaves. The other two groups of needles, one placed in a sealed bag (Green-wet) and the other placed in an open environment (Green-dry), although with the same chlorophyll, showed different temperature due to the different water content. Generally, when needle becomes drier, the radiative temperature becomes higher.

![Fig. 2 The comparisons between the radiative temperatures of needle clusters with different chlorophyll content (left) and water content (right).](image_url)

3.2. Satellite data

The LAI product of EOS MODIS (the MODerate Resolution Imaging Spectroradiometer) in 2008 was selected as a kind of continuous observation and verification data. The monthly variation showed that LAI peaked and was stabilized from the end of July to mid-August, thus chosen as the best time for dynamic monitoring for pests. Considering the historical occurrence information of pests in Aershan region and the seasonal change phenomena, as well as the qualities of remote sensing images, twelve remote sensing images of Landsat-5/7 were ordered as the data sources, including images at August 16, 1998, July 15, 2001, August 3, 2002, August 14, 2003, July 15, 2004, August 8, 2004, June 24, 2005, July 18, 2005, August 27, 2005, August 6, 2006, August 16, 2007 and August 19, 2008. ALOS (Advanced Land Observation Satellite), a
higher spatial resolution (2.5m) data, at August 17, 2008 was also bought in the study for analysis and validation.

A local regression of adaptive methods was performed to fix and restore the Landsat-7 ETM + SLC off data. Polynomial geometric correction was done based on 1:50 000 topographic maps, whose position error was within 0.5 pixels. Based on 6S (Second Simulation of Satellite Signal in the Solar Spectrum) model decoupling atmosphere/land effect, atmospheric correction was performed to calculate the true target radiance and reflectance in visible and near infrared bands. The Dark Object method, using dense vegetation as reference, was used. Clouds were removed by a threshold 0.18 at blue band (TM band 1).

4. REMOTE SENSING INVERSION

4.1. Larch forest identification

The Larch forest covers more than 90% of the forest area in the forest farm. A knowledge-based rule by NDVI, slope and aspect were used to extract the Larch compartment with the C4.5 algorithm. Field validation shows overall accuracy of 92.1%. Figure 3 presents the identified Larch distribution map.

4.2. Inversion of CWC and LAI

First, a Lookup Table (LUT) was built by Five-scale model. Landsat TM3, TM4, and TM5 were the three main output parameters. To match the band response widths and functions, the simulated high-spectral data were re-sampled to multi-spectral data. The input parameters included crown shape factors, LAI, SZA, leaf Chlorophyll and water content.

Second, a four-layer back propagation neural network (BP) was designed and trained by half of the LUT. The input layer had four nodes which represent the three reflectance parameters, and a pre-estimated LAI or CWC respectively. The output layer had two nodes corresponding to CWC or LAI. The number of hidden layers was set to 2 by finding the best performance based on lots of debugging. The first and second hidden layers had six and two nodes respectively. Finally, the BP network, evaluated by the other half of the LUT, was used to inverse the LAI and CWC. The retrieved LAI had the same trend with those of MODIS products and measurements, except the slightly lower value than MODIS LAI. Compared with the measurement of CWC in compartment 61 (2.22 mm), the inversed value were $2.38 \pm 0.26$ (mm), which was acceptable.

4.3. Derivation of TVDI

Derivation of TVDI representing soil moisture based on the feature space between Normalized Difference Vegetation Index (NDVI) and land surface temperature (Ts). The Mono-window algorithm was used to correct the atmospheric and emissivity effect and obtain the Ts from brightness temperature of Landsat TIR band 6. By fitting the dry edge and wet edge, TVDI was calculated for the whole YIERSHILIN forest farm, whose average value varied between 0.4 and 0.6 from 1998 to 2008. Compared with the yearly statistics rainfall data, TVDI showed the similar trend except the data in 2006, which can be explained by the affection of heavy clouds (see Fig. 4).

4.3. Derivation of TVDI

Fig. 4 The comparison between the annual precipitation by ground observation and inversed TVDI inversed from the remote sensing images from 1998 to 2008

5. DECISION RULES

Based on training samples of health or attacked pixels with the three indices, a decision tree was build as a monitoring rule (Fig. 5) to classify the pest-infected pixels based on remote sensing data. The rule should be validated and applied to derive continuous damage map of Larch.

Applying the rules on the image at July 18, 2005 for classification, we found acceptable accuracies to identify the three kinds of pixels: pine moth affected pixels with 82.8%, boring insects affected pixels with 80.3%, and health pixels with 98.7%. Without distinguishing between the two types of victims, the accuracy was 89.7%.
6. CONTINUOUS MONITORING

Based on the rule (see Fig. 5), classifications on the twelve remote sensing images were performed and the annual area statistics was extracted (Fig. 6) for macro-dynamic monitoring, which shows that the Larch forest area of YIERSHI forest farm was declining with a sharp decline in 2003 and recovering after that. In fact, in 2003, a huge outbreak of pine moth occurred. However, great loss of leaf area did not lead to large area of true death of pine trees. In May 2004, Forestry Administration in Aershan took a large area of aerial control, which reduced disaster of Pine Moth. Thus, the Larch forest area soon rebounded in 2004.

![Fig. 6 The area variations of larch forest extracted from remote sensing images in the YIERSHI forest farm](image)

![Fig. 7 The variations of pest-damaged Larch forest area in YIERSHI forest farm](image)

Figure 7 shows the yearly variations of harmed area by pests. It can be seen that Pine caterpillar affected area began to increase from 1998 and reached a peak in 2003. After 2003, the affected area began to decline. The trend is basically consistent with the field survey data and confirms that the aerial control played great effect. The boring insects affected area reached a maximum in 2004 after two consecutive years of large areas of pine moth invasion. The loss of needles resulted in a large number of very weak tree vigor, leading to a large invasion and outbreak of beetles. Thus, a sudden increase in the acreage occurred and a maximum value appeared in 2004, then the area began to decrease.

Without considering the types of pests, all affected compartment was correctly predicted in the five years (2003, 2004, 2007 and 2008). By applying random sampling technique in 2008, the prediction accuracy of pest distribution of 2008 was estimated as 93.2%. If considering the types, the accuracy decreased. The monitoring accuracy of pine moth injured compartments was still acceptable (> 70%), while the predication of trunk pest was only acceptable in 2005 (70%) and 2006 (80%). Lacking of survey data on trunk pests from 2001 to 2004, monitor accuracies in those years can not be obtained. The reason for low accuracy to predict trunk pests may be due to not considering the overlapping effect in the decision rule.

7. DISCUSSION AND CONCLUSION

Although lots of work has been done and some satisfactory conclusion was drawn, it is still far away to understand the mechanism of remote sensing of forest pests. Due to lack of detailed spatial and temporal history of the ground survey data, further in-depth analysis and validation was difficult to perform. In the next step, control experiment at single-tree level considering pathogenic factor and high spectral feature will be done to identify mechanism.

8. REFERENCES


