GOAL PROGRAMMING APPROACH TO ACHIEVE SUSTAINABLE FOREST MANAGEMENT IN MONGOLIA

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KEY WORDS: goal programming, forest resource, sentinel, FI

ABSTRACT: Forest resources are the most important natural resources on this earth, but they are continuously depleting due to the overgrowth of human population, needs, and industrialization, other development activities. Therefore, the conservation of forest resources has been the main problem for sustainable development and several mathematical and remote sensing methods were used to find the optimal way to achieve it. In this research, Forest Index (FI) was applied to determine forest coverage in the study area. The study area (49°15′ to 49°10′N and 104°05′ to 104°15′E) is located in the northern region of Mongolia and consists of mixed forest. Larch Forest dominates 86.12% of forests in the study area. FI methodology was applied for the Sentinel data in order to estimate larch forest coverage. The output map of forest coverage was compared with ground truth measurements and forest cover maps. The agreement between the forest cover map and ground measurement was 85%. Additionally, we used goal programming method to find the optimal harvest volume for Mongolian forest resources based on data containing volume and growth.

1. INTRODUCTION

Mongolia is landlocked country and is located in the central and semi-arid northeastern part of Asia. 8 percent of the total territory of Mongolia is amounted as forested area (FCRD 2017). The northern part of Mongolia has taiga forest covers, which extends to Siberia in Russia in the North. In last decades, one of the important industries in Mongolia is forestry and has great potential nowadays as a source of sustainable livelihoods for the forested provinces.

The regional or global scale, remote sensing techniques always offer an effective way for forest measurement and monitoring. Remote Sensing can be used to measure and monitor develop environmental policies and plans of the research areas (Enkhjargal, 2014). Nowadays many researches for forest cover mapping, forest type, forest degradation, fire of forest, inspected area uses active and passive remote sensing (Mitchell, 2017). In Mongolia, most research focused on using forest inventory statistics to estimate total forest area to further explore remote sensing or sources lacking image-based spatial information (Norovsuren B. R., 2019) and small-scale uncertainties still existed in some related research.

The main goal of this study was to map the change of forest area using satellite image data and the ground truth data (Norovsuren B. R., 2019).
While remote sensing technology must help in providing information to satisfy the needs that forest managers have, remote sensing must be a cost-effective and easily understandable technology (Altangerel, 2019).
Our study shows that the newly developed index is important for monitoring forests in northern Mongolia, which are sparsely populated and inaccessible to rangers and researchers (Norovsuren B. T., 2023).

Regarding to forest and sustainable development, the importance of sustainable forest management has increased. The main concept is to manage a forest according to the principles of sustainable development. Sustainable forest management has to keep the balance between three main goals: ecological, economic, and socia-cultural. In Mongolian case, forest products and utilization are well addressed within legal framework. However, legal regulation and enforcement are found to be weak in practice. The main impacts of forest depletion in Mongolia are caused by unsustainable forest harvesting (both permitted and illegal) for timber and fuelwood, forest fire, insect and disease, and mining. Unsustainable logging and Unsustainable logging and subsequent degradation mainly take place due to illegal activities. Although the official statistics are not available, there is a gap between official supply and demand statistics, which can be explained by the unofficial activities. Currently between 36% and 80% of Mongolia's total timber harvest is categorized as illegal. That is, the government receives no royalties or taxes on this and it severely distorts domestic prices for both construction wood and fuelwood. As a result, this indicates a lack of government policies and sustainable management based on realistic estimates considering potential forest ecological resources and increasing social demand. Also, in the last few years, there has been an increasing tendency to consider forest ecosystems as possible sinks of carbon dioxide (CO_2). In this way, an attempt is done to reduce the dramatic increase of global CO_2 emissions in the industrialized countries and consequently to the mitigation of climate warnings. One of the mathematical techniques that could handle a multipurpose problem is Goal Programming. GP is a special case of linear programming. Therefore, the GP model was applied to determine the optimum standing timber or volume based on multi-criteria decision-making in Khangal soum, Bulgan province, Mongolia. To our knowledge, in 2020, expect (Gompil, 2022) has applied dynamic modeling to control and reduce illegal logging through mathematical modeling based on the actual dynamics of forest resources, there are no mathematical models especially goal programming approach used for Mongolian forest resource depletion and operation.

2. STUDY AREA AND DATASETS

2.1 Study area

The study area is Khangal Soum, Bulgan province where situated in the northern part of Mongolia and borders the Russian Federation. Bulgan province is located in the taiga zone, forest-steppe zone, and steppe zone. Majestic high mountains of Bulgan, Burenkhangai, and Dulaankhaan dominate in the northern part of the province. The north of the province is characterized by alpine forests, gradually blending into the arid steppe plains of the central Mongolian highland. According to the Holdridge life zones system of bioclimatic classification Bulgan is situated in the boreal dry scrub biome (larch, birch, and shrub) where larch is 86.12% and birch is 13.88%. (Altanchimeg, 2019)

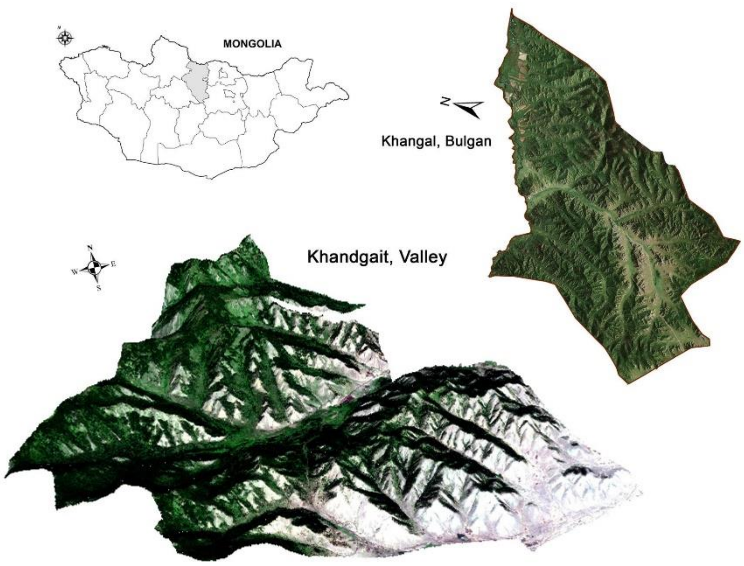

Figure 1. Khangal soum in Bulgan province

2.2 The collected data

We used field data including high, diameter, type of tree and FI data and Satellite Remote Sensing data in this research. (Altanchimeg, 2019)

2.2.1 Field data

Table 1. Larch field data example

Diameter (cm)	High (m)	Diameter (m)
9.5	12	0.10
27.7	16.5	0.28
36.2	18.1	0.36
27.3	15.6	0.27
29.7	16.4	0.30
18	12	0.18
35	18.2	0.35
34	17.8	0.34
34.8	18.1	0.35
30.5	16.7	0.31
31.3	16.9	0.31

Firstly, to calculate the volume of the tree in m^3, we used the table in (Ch. Dorjsuren, 2012), then converted its value to m^3ha^{-1}. Second, we calculated carbon sequestration using a method in (Sharma, 2020). As a result, the total sequestred carbon for larch and birch is 436.196t, 52.726t respectively.

Table 2. Birch field data example

Diameter (cm)	High (m)	Diameter (m)
19.5	18	0.20
34.5	17.1	0.35
27.3	15.2	0.27
22.6	13.1	0.23
24.3	13.9	0.24
23	13.3	0.23
15.5	9.9	0.16
17.7	10.9	0.18
21.3	12.6	0.21
39	19.9	0.39
35.8	18.6	0.36

2.2.2 Forest Inventory data

The systematical national forest inventory (NFI) has been conducted nearly every ten years since the late 1956 and the last national forest inventory was conducted for the period 2013 (FDRE, 2018). The statistics of the national forest inventory in Mongolia are based on large numbers of field plots and are the most important data sources for research on forest. (Altanchimeg, 2019)

3. METHODOLOGY

We used Remote sensing methodology for the middle-resolution satellite data. Assessment processed with the layer of the data such as Forest taxation data of the FRDC, Google Earth Pro and Bing map used SNAP and GIS software's. We used forest index for the Sentinel satellite data when we define forest cover area of study area. (Altanchimeg, 2019)

3.1 Data pre-processing

In the current study, the Sentinel-2 data were pre-processed using the SNAP v. 4.0.0. Selection of the proper resampling technique for registration of multidate Landsat imagery can be important to digital classification accuracy in mountainous forest areas (Mitchell et al., 2017). Resampling is usually done for the digitizing the pixel values from the existing cell values (Roy et al., 2016). Resampling was done between LST from Landsat-8 and FI from Sentinel-2 satellite. (Altanchimeg, 2019)

3.2 Estimation Algorithm for forest cover

Cohen (1991) suggests that the first true vegetation index was the Simple Ratio (SR), which is the ratio of red reflected radiant flux (ρred) to near infrared radiant flux (ρnir) as described in Birth and McVey (1968) as:

$$RVI = {}^{NIR}/_{RED} \qquad (1)$$

Cohen (1991) suggests that the first true vegetation index was the Simple Ratio (SR), which is the ratio of red reflected radiant flux (ρred) to near infrared radiant flux (ρnir) as described in Birth and McVey (1968) as:

$$FI = \left(\frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}} - \mathrm{L}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}}}\right)\left(\frac{C_1 - \rho_{NIR}}{C_2 + \rho_{green}}\right) \qquad (2)$$

where L = 0.01,
C1 = 1,
C2 = 0.1

The parameter L is a very small value and the introduction of which can effectively lower the NDVI of water while has little impact on the NDVI of vegetation. C1 and C2 are empirical parameters used to scale the function. Thus, the range of the FI is from minus infinity to 7. FI gives a positive value on forested area and vice versa negative value on the non-forested area. (Altanchimeg, 2019)

3.3 Goal programming model

Goal programming (GP) is an extension of Linear programming in which targets are specified for a set of constraints. The GP model has an objective function, constraints (called goal constraints), and the same nonnegativity restriction on the decision variables (and deviation variables) as the LP model. It should be mentioned that some GP researchers feel that the term objective function is not an accurate term and the terms achievement function or underachievement function should used in its place. A generally accepted statement of this type of GP model was presented in Charnes and Cooper (1997). (Schniederjans, 2012)

$$Minimize: z = \sum_{i \in m} (d_i^+ + d_i^-) \qquad (3)$$

$$subject\ to: \sum_{j=1}^{n} a_{ij} x_j - d_i^+ + d_i^- = b_i \qquad (4)$$

where d_i^+ is called *positive deviation variable* and d_i^- is called a *negative deviation variable.*

3.4 Formulating GP model

We use functions (1) and (2) to formulate GP model. First, we determine the following constraint functions,

$$X_1 + X_2 \geq 52 \qquad (5)$$

Equation 3 is minimum total feasible volume ($m^3 \cdot ha^{-1}$), where X_1 is volume of larch, X_2 is volume of birch.

$$X_1 \geq 46 \qquad (6)$$

Equation 4 is minimum suitable volume of larch. It should be equal or greater than 45 $m^3 \cdot ha^{-1}$.

$$X_2 \geq 5 \qquad (7)$$

Equation 5 is minimum suitable volume of birch. It should be equal or greater than 5 $m^3 \cdot ha^{-1}$.

$$1.378X_1 + 1.466X_2 \geq 71 \qquad (8)$$

Equation 6 is minimum sequestrated carbon ($t \cdot ha^{-1}$). The decision variable coefficients (X_1, X_2) are the sequestrated carbon that calculated for each species. We determine the negative or positive from the goal based on the properties of the constraint. If the initial constraint or inequality is greater than a quantity, then the negative deviation should be included in the equation. This negative deviation should be written on the left-hand side of the equation and the inequality will be changed to equality. In case the initial constraint is less than a quantity, then positive deviation should be substracted from the left-hand side of the equation. On the other hand, the signs D_i^- or D_i^+ can be added to relations 3 to 6 in the different above-mentioned cases. According to the properties of the constraints in this work, we did not have any positive deviations from the goal. Thus, the following new equations are determined.

$$X_1 + X_2 + D_{tv}^- = 52$$

$$X_1 + D_l^- = 45.81$$

$$X_2 + D_b^- = 5.21$$

$$1.378X_1 + 1.466X_2 + D_c^- = 7$$

where, D_{tv} is negative deviation of total volume, D_l is negative deviation of larch volume, D_b is negative deviation of birch volume, D_c is negative deviation of sequestrated carbon. The aim objective function was to minimize the unfavourable deviation from the goal. Therefore, the following function was determined.

$$minz = D_{tv}^- + D_l^- + D_b^- + D_c^- \qquad (9)$$

4. RESULTS

4.1 Forest index

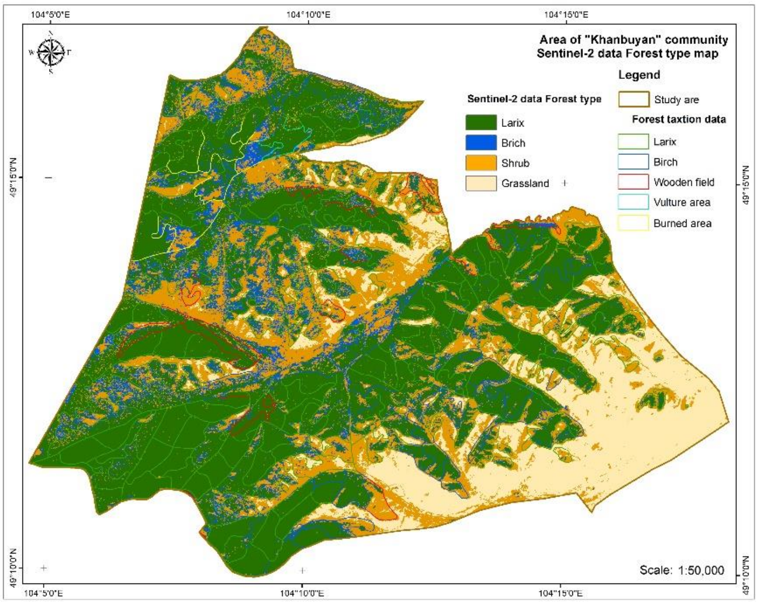

Figure 2. Forest cover map combined Forest taxation data

Table 3. National forest inventory NFI and forest cover

Body 2018	*Area in ha*
Study area	11540
NFI	8184.7
Forest cover	6434.4
Non forest cover	6905.6

Study area statistics are provided in (Table 3). The defined NFI area cover 15% of study area. In total the study area is covered by about 6434.4 hectares of boreal forest considering the 10 m^2. For the validation the output map FI (figure 2) was compared with NFI data using confusion matrix (Table 4). There is a good agreement with forest inventory data which is 85% (Altanchimeg, 2019).

Table 4. Confusion matrix and accuracy estimates

Sentinel 2 /FI/	***National forest inventory***			
		Forest	Non-Forest	∑
	Forest	1286	695	1981
	Non-Forest	819	1431	2250
	∑	2105	2126	4231
	Overall Accuracy			85%

4.2 Goal programming model

The results of GP model are shown in Table 4 that solved by LINGO software. It shows that total optimum volume is $51.02m^3 \cdot ha^{-1}$, with its negative deviation of the goal is $0.98m^3 \cdot ha^{-1}$.

Table 5. Result of goal programming model

Variable	Value
D_{tv}	0.98
D_l	0
D_b	0
D_c	0.236
X_1	45.81
X_2	5.21

5. CONCLUSIONS

FI map was overlaid and compared on Inventory map. The validation result is reasonable (Table 4). These results indicates that the FI can effectively highlight forest cover. Advantage of using FI allow us to monitor forest for every 5 years and compare with NFI data. FI can also analyse seasonal change for different forest in the region. Overall, the research indicates that modern RS techniques and technologies are reliable tools for forest monitoring and management.

Also, this research was done to determine the optimal value based on two different factors, namely minimum acceptable volume and carbon sequestration. In (Limaei, 2014), the goal programming approach is applied to determine the optimal harvest volume for the Iranian Caspian Forest. They also used regression analysis to their data to derive growth and wood price. Also, LINGO software is used in this work. Hence, there is some similarity between their model and this research.

However, the GP model is one of the techniques that could handle multipurpose management, as it was discussed before. This technique is applied to solve forest management problems with different goals and criteria in different countries.

The decision-makers can use this method for sustainable forest management to consider the economics, environmental, and social aspects of forest management.

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