International Journal of Architecture and Urbanism Vol. 10, No. 02 (2026) 282 – 292

International Journal of Architecture and Urbanism

Journal homepage: https://talenta.usu.ac.id/ijau

Study On The Development and Application of A Felling Rate Prediction Model in Forest Construction Design

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ARTICLE INFO

Article history:
Received 4 August 2025
Revised 6 April 2026
Accepted 29 July 2026
Available online 30 August 2026

E-ISSN: 2622-1640
P-ISSN: 2622-0008

How to cite:
Nam, P. J et al. Study On The Development and Application of A Felling Rate Prediction Model in Forest Construction Design. International Journal of Architecture and Urbanism. 2026. 10(2):282-292.

http://doi.org 10.32734/ijau.v10i2.22342

ABSTRACT

Accurate estimation of felling rates is essential for balancing timber production, forest regeneration, and ecological sustainability, particularly where long-term inventory records are limited. This study developed and applied a first-order grey prediction model, GM(1,1), to forecast annual felling rates in Kophung County, Jagang Province, using five observations from 2019–2023. Models were constructed for Area 3 and for the regional mean of ten management areas. Model performance was evaluated using residuals, absolute percentage errors, mean absolute percentage error, and in-sample fitting accuracy. The Area 3 model achieved 97.83% fitting accuracy and predicted a 2024 felling rate of 7.461%. The regional model achieved 96.58% accuracy and predicted 7.545%. The results show that GM(1,1) can provide transparent short-term forecasts under small-sample conditions. However, the estimates should support, rather than replace, decisions based on forest inventory, growth, regeneration, ecological constraints, and independent validation before operational adoption in sustainable forest construction planning and management practice.

Keywords: felling rate, forest construction, grey prediction, GM(1,1), sustainable forestry

1. Introduction

Forests perform ecological, economic, and social functions by conserving biodiversity, regulating water and soil conditions, storing atmospheric carbon, supplying timber, and supporting local livelihoods. The long- term continuity of these functions depends on the ability of forest managers to balance timber removalwith forest growth and regeneration. Therefore, forest construction design should not be limited to determining the physical arrangement of forest compartments, roads, plantations, and harvesting operations. It should also provide a quantitative basis for determining the timing, scale, and intensity of felling activities. Inaccurate estimation of the allowable felling rate may result in either excessive harvesting, which reduces growing stock and ecological stability, or insufficient harvesting, which can limit the economic utilization of mature forest resources.

Recent forestry studies have increasingly emphasized that forest management performance must be evaluated by considering both production efficiency and ecological outcomes. He et al. demonstrated that forest carbon-sink development is closely related to forest area, management inputs, and the efficiency with which forestry resources are allocated [1]. Tan et al. similarly showed that forestry eco-efficiency is affected by differences in resource endowment, investment, management capacity, and regional development conditions [2].

Furthermore, Liu et al. reported substantial spatial and temporal differences in forest carbon-storage efficiency, indicating that the condition and performance of one forest area cannot necessarily be generalized to another [3]. These findings underline the importance of using area-specific data when determining future harvesting intensity.

One of the principal quantitative indicators used in forest production planning is the felling rate. In this study, the felling rate is defined as the proportion of felled timber volume or felled trees relative to the total forest growing stock or total number of trees during a specified period. The indicator provides a direct representation of harvesting intensity and can be used to support decisions concerning annual timber output, regeneration requirements, labor allocation, transportation capacity, and the scheduling of silvicultural operations. When the felling rate is maintained within an appropriate range, forest production can be coordinated with stand growth and regeneration. Conversely, a rate that is determined without adequate analysis may produce an imbalance between harvesting and forest recovery.

The quantitative prediction of felling rates may be performed using time-series models, regression analysis, Markov models, artificial neural networks, machine-learning algorithms, or combinations of these approaches. However, many conventional statistical and data-driven models require long observation sequences, stable data-generating processes, or large training datasets. These conditions are not always available in practical forest management. Forest inventory records may be incomplete, measurement practices may have changed, and annual observations may be limited because forest growth and management cycles are relatively long. The datasets presented in Table 1 and Table 2 illustrate this problem because only five annual observations are available for each study unit.

Table 1. Investigative table of felling rate in the area

Year	2019	2020	2022	2022	2023
No.	1	2	3	4	5
Felling rate	7.76	6.82	7.43	7.16	7.29

Table 2. Investigative table of felling rate by area in the region

Year / By area	2019	2020	2022	2022	2023
Area 1	6.56	6.31	7.03	7.21	7.21
Area 2	6.84	6.32	7.13	6.74	7.32
Area 3	7.76	6.82	7.43	7.16	7.29
Area 4	6.41	6.31	6.86	6.44	6.73
Area 5	7.45	6.61	7.36	7.27	7.34
Area 6	6.76	6.23	7.54	5.65	7.36
Area 7	7.64	7.19	7.56	7.68	7.73
Area 8	7.08	5.25	6.76	6.37	7.40
Area 9	6.34	6.08	7.42	6.38	7.45
Area 10	6.73	5.21	6.82	6.33	6.81
Average	6.957	6.233	7.191	6.763	7.264

Grey-system forecasting provides an alternative approach for systems characterized by limited, incomplete, or partially known information. The conventional GM(1,1) model transforms an irregular original sequence through a first-order accumulated generating operation and then approximates its underlying development pattern using a first-order differential equation. Its principal advantages are computational simplicity, transparent parameter estimation, and the ability to construct a forecasting model from a small number of observations. Recent research confirms that GM(1,1) remains relevant for small-sample forecasting, although its performance may decrease when the observed system contains strong fluctuations, structural changes, or nonlinear behavior [4][5].

The accumulated generating operation is important because annual forest-management data may fluctuate in response to harvesting schedules, weather conditions, accessibility, management interventions, and changes in timber demand. The six-period illustrative sequence presented in Fig. 1 demonstrates how a highly fluctuating original sequence becomes a monotonically increasing sequence after accumulation. The accumulated sequence does not remove the information contained in the original observations; instead, it reduces the influence of short-term irregularity so that the dominant development tendency can be represented mathematically.

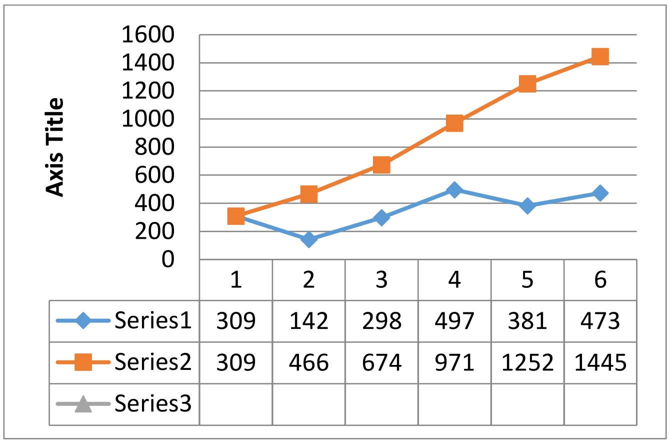

Figure 1. Characteristics of the variation in the felling rate in the area by year

Developments in grey-system research have attempted to overcome several limitations of the conventional model. Multivariate grey models can incorporate explanatory variables and use data-filtering or optimization procedures to improve forecasting stability [6]. Adaptive GM(1,1) models can modify the effective sequence length, place greater emphasis on recent observations, and apply stationarity or residual-correction mechanisms when the characteristics of a time series change [5]. Nevertheless, the conventional GM(1,1) model remains useful as an initial forecasting method when the research objective is to produce an interpretable prediction from a short univariate dataset. Its simple structure also makes the model suitable for forestry planning institutions with limited computational resources.

Despite the growing application of quantitative models to forest carbon storage, forest-management efficiency, and environmental performance, fewer studies have addressed the direct prediction of operational felling rates using very short annual sequences. Existing studies generally focus on carbon-sink efficiency, regional forestry productivity, forestland management, or long-term carbon-storage trends [1][2][3]. These studies provide important information for forestry policy, but they do not directly produce annual felling-rate estimates that can be incorporated into forest construction design. Consequently, a methodological gap remains between broad evaluations of forestry performance and the operational calculation of harvesting intensity.

The present study addresses this gap by developing and applying a GM(1,1) model to predict the felling rate in Kophung County, Jagang Province, the Democratic People's Republic of Korea. The analysis is conducted at two levels. First, the model is applied to the annual felling-rate sequence of a selected management area, referred to as Area 3. The corresponding observations are presented in Table 1. Second, the model is applied to the annual mean felling rate calculated from ten management areas, as presented in Table 2. The regional annual variation and its accumulated sequence are illustrated in Fig. 2.

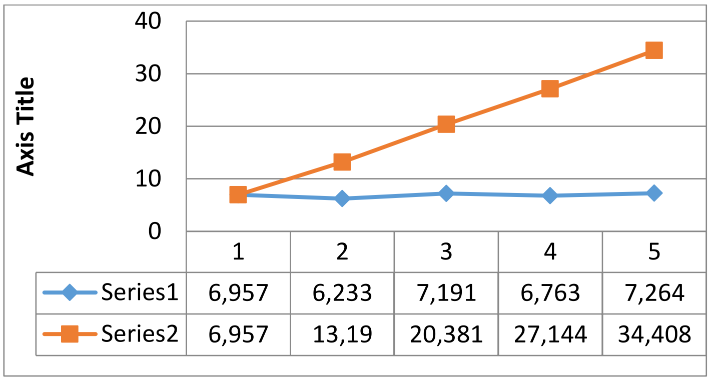

Figure 2. Characteristics of the variation in felling rate in the area by year.

The study aims to formulate a transparent mathematical procedure for felling-rate prediction, evaluate the ability of GM(1,1) to reconstruct the observed annual sequence, and generate a short-term forecast that can serve as a technical reference for forest construction planning. The model is evaluated using absolute residuals, relative errors, mean absolute percentage error, and fitting accuracy. By comparing the area-level and regional models, the study also examines whether a forecast based on a specific management area differs from a forecast based on aggregated regional data. The resulting prediction is intended to support, rather than replace, professional decisions based on forest inventory, stand age, species composition, annual increment, regeneration capacity, ecological restrictions, and applicable forest-management regulations.

2. Method

The study used annual felling-rate data collected from ten forest-management areas in Kophung County, Jagang Province. The observation period covered five consecutive years from 2019 to 2023. Because the original tables contained two columns labeled 2022, the chronological sequence was standardized as 2019, 2020, 2021, 2022, and 2023. This correction preserves the five consecutive annual observations required by the model and ensures that the subsequent value generated after the 2023 observation represents the forecast for 2024.

The felling rate was calculated as the percentage of felled growing stock relative to total forest growing stock. It was expressed as

$$P = \frac{t}{T} \times 100 \quad (1)$$

Where P is the felling rate in percent, t is the volume or number of trees felled during the observation period, and T is the total forest growing stock or total number of trees in the corresponding management unit. Both t and T must be expressed using the same unit, such as cubic metres or number of trees.

Two datasets were used in the model application. The first dataset consisted of the felling rates for Area 3, namely 7.76%, 6.82%, 7.43%, 7.16%, and 7.29% for 2019–2023, respectively. These values are presented in Table 1. Area 3 was used as the area-level case because the original study identified this area as the basis of the first model application. The second dataset consisted of the annual mean felling rates calculated from all ten areas. The regional mean values were 6.957%, 6.233%, 7.191%, 6.763%, and 7.264%, respectively, as reported in Table 2.

Table 2 also provides the spatial distribution of the annual felling rates. The data indicate that the ten areas did not have identical harvesting patterns. Consequently, the regional mean was treated as an aggregate planning indicator rather than as a replacement for area-specific information. The regional original sequence and its accumulated values are visualized in Fig. 2. The figure was used to compare the relatively irregular annual observations with the smoother accumulated sequence generated by the grey-model procedure.

The conventional GM(1,1) method was selected because only five annual observations were available for each analysis. GM(1,1) denotes a first-order grey model containing one dependent variable. The method is designed to extract the dominant development tendency of a short and partially known data sequence. Nevertheless, because univariate grey models may perform poorly for strongly fluctuating or structurally unstable sequences, the model output was subjected to residual-error evaluation [4]. The conventional model was retained instead of a more complex optimized or adaptive model because the objective was to establish a simple and reproducible forecasting procedure suitable for preliminary forest planning. More advanced multivariate and adaptive approaches may subsequently be used when longer series and explanatory variables become available [5][6].

Let the original non-negative felling-rate sequence be defined as

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\right\} \tag{2}$$

Where $x^{(0)}(k)$ is the observed felling rate in year k, and $n = 5$ for both datasets. The superscript (0) denotes the original sequence. For Area 3, the original sequence was

$$X_A^{(0)} = \{7.76,\ 6.82,\ 7.43,\ 7.16,\ 7.29\} \tag{3}$$

For the regional analysis, the original sequence was

$$X_R^{(0)} = \{6.957,\ 6.233,\ 7.191,\ 6.763,\ 7.264\} \tag{4}$$

A first-order accumulated generating operation, or 1-AGO, was applied to reduce random fluctuation in each original sequence. The accumulated sequence was defined as

$$X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right\} \tag{5}$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1, 2, \ldots, n. \tag{6}$$

The accumulated Area 3 sequence was therefore

$$X_A^{(1)} = \{7.76,\ 14.58,\ 22.01,\ 29.17,\ 36.46\} \tag{7}$$

whereas the accumulated regional sequence was

$$X_R^{(1)} = \{6.957,\ 13.190,\ 20.381,\ 27.144,\ 34.408\} \tag{8}$$

The smoothing effect of accumulation is conceptually illustrated in Fig. 1. In the illustrative example, the original six-period felling sequence varies considerably from one period to another, whereas its accumulated sequence forms a continuously increasing curve. Similarly, Fig. 2 shows that the accumulated regional felling-rate sequence has a clearer development direction than the original annual values.

An adjacent mean sequence, also referred to as the background-value sequence, was then constructed from the accumulated data:

$$Z^{(1)} = \left\{ z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n) \right\} \tag{9}$$

where

$$z^{(1)}(k) = \lambda x^{(1)}(k) + (1-\lambda) x^{(1)}(k-1) \tag{10}$$

The conventional background coefficient was set to $\lambda = 0.5$, resulting in

$$z^{(1)}(k) = \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k-1) \right] \tag{11}$$

The GM(1,1) grey differential equation was expressed as

$$x^{(0)}(k) + a z^{(1)}(k) = b, \qquad k = 2, 3, \ldots, n \tag{12}$$

where   is the development coefficient and   is the grey input or control coefficient. The coefficient represents the direction and rate of development of the sequence, whereas   represents the external or endogenous driving quantity summarized by the model.

The parameters were estimated using the least-squares method. Equation (12) was written in matrix form as

$$Y = B\hat{\theta} \tag{13}$$

Where

$$Y = \left[x^{(0)}(2)\ x^{(0)}(3) \vdots x^{(0)}(n) \right], \qquad B = \left[-z^{(1)}(2) \quad 1\ -z^{(1)}(3) \quad 1 \vdots \quad \vdots -z^{(1)}(n) \quad 1 \right] \tag{14}$$

and

$$\hat{\theta} = \left[\hat{a}\ \hat{b} \right] \tag{15}$$

The estimated parameter vector was obtained from

$$\hat{\theta} = \left(B^T B\right)^{-1} B^T Y \tag{16}$$

After estimating   and , the whitened differential equation corresponding to the grey model was written as

$$\frac{dx^{(1)}}{dt} + a x^{(1)} = b. \tag{17}$$

The time-response function of the accumulated sequence was then calculated as

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a}, \qquad k = 0, 1, \ldots, n \tag{18}$$

The predicted values on the original scale were recovered through the inverse accumulated generating operation:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{19}$$

For $k = 0$, the reconstructed initial value was set equal to the first observed value. Values obtained for $k = 1, ..., 4$ represented reconstructed felling rates for the remaining observed years, whereas the value obtained for $k = 5$ represented the one-step-ahead prediction for 2024. This indexing avoids treating a fitted value for 2023 as an independent forecast.

The suitability of the model for extrapolation was initially examined using the magnitude of the estimated development coefficient. In accordance with the modelling rule adopted in the original study, a value of $|a| < 0.3$ was regarded as indicating that GM(1,1) could be used for medium-term prediction. A value between 0.3 and 0.5 would indicate greater suitability for short-term prediction, whereas a larger magnitude would require caution. This coefficient criterion was treated only as a preliminary diagnostic because recent studies show that model reliability also depends on the regularity, stationarity, and fluctuation structure of the original sequence [4][5].

Model fit was evaluated by comparing each observed value with its reconstructed value. The residual error was calculated as

$$e(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \tag{20}$$

and the absolute residual was calculated as

$$\Delta(k) = \left| x^{(0)}(k) - \hat{x}^{(0)}(k) \right| \tag{21}$$

The absolute percentage error for each reconstructed observation was calculated using

$$APE(k) = \frac{\left| x^{(0)}(k) - \hat{x}^{(0)}(k) \right|}{x^{(0)}(k)} \times 100\% \tag{22}$$

Because the first observation was used as the model's initial condition and was reproduced exactly, it was excluded from the average-error calculation. The mean absolute percentage error was therefore calculated as

$$MAPE = \frac{1}{n-1} \sum_{k=2}^{n} APE(k) \tag{23}$$

For consistency with the original manuscript, model fitting accuracy was expressed as

$$Accuracy = 100\% - \text{MAPE} \tag{24}$$

This accuracy measure represents descriptive in-sample fitting performance rather than a statistical confidence level. It does not indicate the probability that the future felling rate will equal the predicted value. A valid confidence interval would require additional assumptions concerning the residual distribution and substantially more observations. Likewise, independent predictive validity would require one or more observations to be withheld from model estimation.

The complete modelling procedure was applied separately to the Area 3 sequence in Table 1 and the regional mean sequence derived from Table 2. The analysis consisted of constructing the original sequence, performing 1-AGO, calculating the adjacent mean sequence, estimating and , generating reconstructed values, conducting residual-error testing, and calculating the one-step-ahead felling-rate forecast. The figures were used to demonstrate the transformation of the annual observations: Fig. 1 illustrates the general smoothing effect of cumulative generation, whereas Fig. 2 presents the transformation of the regional felling-rate data used in the empirical analysis.

All calculations were performed using double-precision numerical operations. Intermediate values were retained to at least six decimal places to reduce rounding error, while reported felling rates were rounded to three decimal places. The forecast was interpreted as a technical reference for annual forest construction and harvesting planning. It was not treated as an allowable-cut determination independent of forest inventory. Operational adoption of the predicted rate should additionally consider growing stock, net annual increment, stand maturity, species composition, regeneration status, terrain, accessibility, biodiversity protection, carbon-storage objectives, and applicable forest-management regulations.

3. Result and Discussion

The annual felling rates recorded in Area 3 of Kophung County during the 2019–2023 observation period were 7.76%, 6.82%, 7.43%, 7.16%, and 7.29%, respectively. These values produced an average felling rate of 7.292%, with the lowest value occurring in 2020 and the highest value in 2019. The year-to-year pattern was not monotonic because the felling rate decreased sharply between 2019 and 2020, increased in 2021, and subsequently fluctuated within a narrower range. This variation indicates that the original sequence did not present a sufficiently clear linear trend for direct extrapolation. After applying the first-order accumulated generating operation, the original sequence was transformed into the cumulative sequence of 7.76, 14.58, 22.01, 29.17, and 36.46. The accumulated sequence exhibited a smooth and consistently increasing trajectory, demonstrating that the accumulated generating operation effectively reduced short-term variation and revealed the underlying development pattern of the observed felling rate.

Parameter estimation using the least-squares procedure produced a development coefficient $a = -0.015678$ and a grey input coefficient $b = 6.830600$ for Area 3. The absolute value of the development coefficient was below the threshold of 0.3 adopted in this study, indicating that the GM(1,1) model was suitable for short- and medium-term extrapolation of the available sequence. The reconstructed felling rates for 2019–2023 were approximately 7.760%, 7.007%, 7.118%, 7.230%, and 7.344%, respectively. Except for the first observation, which functions as the initial condition of the grey model, the relative errors were approximately 2.74%, 4.20%, 0.98%, and 0.75%. The resulting mean absolute percentage error was approximately 2.17%, corresponding to an in-sample fitting accuracy of approximately 97.83%. The relatively small residuals show that the model reproduced the general level and direction of the observed felling-rate sequence despite the limited number of annual observations.

Using the estimated model, the felling rate for Area 3 in 2024 was predicted to be approximately 7.461%. This represents an increase of approximately 0.171 percentage points, or 2.34%, compared with the observed value of 7.29% in 2023. The forecast therefore suggests a moderate increase rather than a substantial change in harvesting intensity. From a forest-planning perspective, this relatively stable development pattern can support preliminary calculations of harvesting volume, labor allocation, transportation requirements, regeneration activities, and annual forest construction schedules. Nevertheless, the predicted rate should not be interpreted as an automatically permissible harvesting rate because the final felling decision must also account for standing volume, annual forest increment, age-class structure, species composition, regeneration capacity, ecological protection requirements, and the condition of individual forest compartments.

The regional analysis was based on the annual averages calculated from ten areas. The regional fellingrates for 2019–2023 were 6.957%, 6.233%, 7.191%, 6.763%, and 7.264%, respectively, with an overall five- year average of 6.8816%. The raw values again displayed considerable annual fluctuation. In 2023, for example, the rates among the ten areas ranged from 6.73% in Area 4 to 7.73% in Area 7. This one- percentage-point difference demonstrates that a regional mean can conceal substantial spatial variability in stand conditions and harvesting practices. Consequently, regional forecasts should be interpreted together with area-specific assessments rather than being uniformly applied to all forest compartments.

The accumulated regional sequence was 6.957, 13.190, 20.381, 27.144, and 34.408. Estimation of the regional GM(1,1) model produced $a = -0.038317$ $b = 6.083029$ The reconstructed annual values were approximately 6.957%, 6.473%, 6.726%, 6.988%, and 7.261%. Relative errors for the second to fifth observations were approximately 3.85%, 6.47%, 3.33%, and 0.04%, respectively. These errors resulted in a mean absolute percentage error of approximately 3.42% and an in-sample fitting accuracy of approximately 96.58%. Although the regional fitting accuracy was slightly lower than that obtained for Area 3, the error remained sufficiently small for a preliminary planning model based on only five observations. The largest error occurred for the 2021 observation, indicating that the conventional GM(1,1) model was less capable of reproducing the relatively sharp increase from 6.233% to 7.191%.

The corrected regional forecast for 2024 was approximately 7.545%, rather than 7.846% as reported in the original calculation. The predicted value is approximately 0.281 percentage points, or 3.87%, higher thanthe observed regional average of 7.264% in 2023. Both the area-level and regional models thereforeindicate a moderate upward tendency for 2024. The regional prediction is slightly higher than the forecast for Area 3, suggesting that the combined development pattern of the other areas may exert an upward influence on the overall felling rate. However, the spatial variation shown in the observed data indicates that area-level conditions should remain the primary basis for operational decisions, while the regional model should be used for strategic coordination and aggregate resource planning.

The results support the use of GM(1,1) as an initial forecasting instrument when forest-management records are short or incomplete. Grey models can be developed using substantially fewer observations than many conventional statistical or machine-learning models, making them relevant for locations where systematic forest inventories have only recently been established. Recent applications have similarly demonstrated that grey prediction can support environmental and carbon-management forecasting under limited-data conditions [1][6][7]. The accumulated generating operation is particularly useful for reducing the apparent irregularity of a short sequence and identifying its dominant direction. In the present study, this operation transformed two visibly fluctuating annual sequences into cumulative series that could be represented by first-order grey differential equations.

Nevertheless, the high fitting percentages obtained in this study must be interpreted carefully. Values of 97.83% and 96.58% represent in-sample fitting accuracy calculated as 100% - MAPE; they do not represent statistical confidence levels or probabilities that the forecasts will occur. All five observations were used to estimate the model parameters, and no independent observations were reserved for out-of-sample validation. Therefore, comparison of the reconstructed 2023 value with the observed 2023 value cannot be considered an independent forecast test. A more rigorous evaluation would use a rolling-origin procedure in which the model is initially estimated from earlier observations and then tested against one or more withheld years.

This limitation is particularly relevant because the conventional GM(1,1) formulation performs most effectively when the underlying sequence follows a relatively stable exponential development pattern. Its accuracy can deteriorate when data contain abrupt changes, periodic variation, structural breaks, or strong external disturbances [4]. The observed felling rates were affected by alternating increases and decreases, particularly at the regional level. The relatively good fitting results therefore demonstrate the model's ability to reproduce the general level of the series, but they do not establish that the model can anticipate unexpected disturbances such as forest fires, pest outbreaks, extreme weather, policy changes, road-access limitations, or sudden changes in timber demand.

Recent developments in grey-system forecasting have addressed these weaknesses by introducing adaptive sequence lengths, stationarity testing, dynamic background values, residual correction, fractional accumulation, and optimization algorithms. Adaptive GM(1,1) models can assign greater importance to recent observations and adjust the modeling window when the characteristics of a time series change [5]. Optimized multivariate grey models can also incorporate explanatory variables and reduce noise before parameter estimation [6]. These developments suggest that future felling-rate models should consider forest accumulation, annual increment, mature forest area, tree mortality, regeneration success, climatic variables, and management interventions rather than relying exclusively on historical felling rates.

The practical reliability of the forecast also depends on the quality of the underlying forest inventory. Research on forest carbon-stock estimation has shown that measurement error, parameter uncertainty, model residuals, and spatial sampling can contribute substantially to total estimation uncertainty [8]. Therefore, even a forecasting equation with a low residual error may produce unreliable management recommendations when its input data are incomplete or inconsistently measured. Integrating permanent sample-plot observations with satellite, synthetic aperture radar, or other remote-sensing information could improve the estimation of forest accumulation and provide more frequent updates for the felling-rate model. Such integration would also allow predicted harvesting intensity to be evaluated against changes in biomass and carbon stocks.

The results further indicate that a single regional average should not replace compartment-level analysis. Differences among the ten areas may reflect variations in stand age, dominant species, stocking density, terrain, road accessibility, silvicultural treatment, and management objectives. A hierarchical forecasting framework would therefore be more appropriate, with separate GM models developed for each area and the resulting forecasts subsequently aggregated for regional planning. This approach would retain local information while ensuring that the sum of area-level harvesting activities remains consistent with regional sustainability objectives.

Overall, the corrected calculations demonstrate that GM(1,1) can provide a transparent and computationally simple preliminary estimate of future felling rates. The model predicted a 2024 felling rate of approximately 7.461% for Area 3 and 7.545% for the entire study region. These values indicate a moderate upward tendency but should be treated as planning references rather than definitive harvesting prescriptions. The principal contribution of the model lies in its ability to generate an interpretable short-term forecast from a very limited dataset. Its application in forest construction design will become more scientifically robust when longer observation series, independent forecast validation, uncertainty intervals, spatially explicit forest-inventory data, and comparisons with alternative forecasting models are incorporated.

4. Conclusion

This study developed and applied a conventional GM(1,1) model to estimate short-term felling rates using limited annual observations from Kophung County, Jagang Province. The accumulated generating operation successfully transformed the fluctuating original sequences into smoother development patterns that could be represented using first-order grey differential equations. The results demonstrate the practical value of grey-system modelling for forest-management units where long and consistent time-series records are unavailable. The Area 3 model produced an in-sample fitting accuracy of 97.83% and predicted a felling rate of approximately 7.461% for 2024. The model based on the regional mean of ten management areas achieved an accuracy of 96.58% and predicted a regional felling rate of approximately 7.545%. Both forecasts indicate a moderate upward tendency compared with the observed 2023 values. The relatively low fitting errors suggest that GM(1,1) can reproduce the dominant short-term development pattern of the available felling-rate data. The findings provide a transparent quantitative reference for estimating harvesting intensity, production scale, regeneration requirements, labor allocation, and annual forest-construction schedules. Nevertheless, the predicted rates should not be interpreted as independently determined allowable-cut levels. Operational harvesting decisions must also consider standing timber volume, net annual increment, stand age, species composition, regeneration capacity, biodiversity conservation, carbon-storage objectives, terrain, accessibility, and applicable forest-management regulations. The study is limited by the use of only five annual observations, the absence of independent out-of-sample validation, and the univariate structure of the conventional GM(1,1) model. The reported accuracy values represent in-sample fitting performance rather than statistical confidence probabilities. Future research should incorporate longer observation periods, rolling-origin validation, uncertainty intervals, compartment-level forest inventory data, and comparisons with adaptive, fractional-order, multivariate grey, statistical, and machine-learning models. Including climatic, silvicultural, ecological, and socioeconomic variables would further improve the robustness and management relevance of felling-rate predictions.

5. Acknowledgements

The authors acknowledge the institutional support provided by the Basic Research Institute for Architectural Design, Pyongyang University of Architecture, during the preparation of this study.

6. Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the research, analysis, or interpretation of the results reported in this article.

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