Doctoral Dissertation

Research on Road Asset Deterioration in Nepal by Applying Hazard Models
(ハザードモデルを適用したネパールにおける道路資産の劣化に関する研究)

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DEDICATION

"मातृ देवो भव । पितृ देवो भव । आचार्य देवो भव ।"

Revere your mother as God. Revere your father as God. Revere your teacher as God."

This dissertation is dedicated with deep respect and profound gratitude to individuals whose unwavering love, guidance, and support have been the foundation of my life.

To my beloved parents, Mrs. Prabha Laxmi Shakya and Mr. Ganesh Man Shakya, whose selfless love, blessings, values, and sacrifices have shaped my character and aspirations. Your constant encouragement and belief in me have been my greatest strength.

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Chapter 1 : Introduction

1.1 Research Background

Nepal is a landlocked country and relies heavily on its road network for economic growth and social connectivity, built collaboratively by the Federal, Provincial, and Local governments. Road infrastructure is vital in facilitating trade, transportation, healthcare access, education, and overall connectivity among remote and urban regions. In a geographically diverse country like Nepal, where mountainous and hilly terrain dominates and alternative modes of transport such as airways, railways, and waterways are limited, the road network serves as the primary means of connectivity and livelihood. Referring to the 16th Five-Year Plan of Nepal (2024/25 to 2028/29), we anticipate significant growth in the road asset over the next five years [1].

In recent decades, there is significant growth in Strategic Road Network (SRN) of Nepal which has improved connectivity to different parts of the country, yet the sustainability of this infrastructure remains a critical concern due to natural hazards, climate variability, and limited maintenance resources. Among various factors, road deterioration caused by environmental and operational factors such as traffic is a major issue, especially in Nepal's mountainous and mid-hill regions with heavy traffic. Additionally, roads in Nepal are subject to heavy monsoon rainfall, fragile geology, and insufficient drainage systems. These conditions accelerate pavement degradation and directly affect road safety, leading to frequent road closures, economic loss, and reduced accessibility.

Road Asset Management (RAM) practices are introduced to address these issues. A dedicated RAM branch has been established in Department of Road (DOR), but it is not fully functional due to data limitations, institutional capacity, analytical tools, and software. Therefore, there is a strong need to develop practical deterioration models that reflect local conditions and integrate hazard-based approaches to support effective decision-making in road maintenance planning [2].

1.2 Research Statement

Although the existence of RAM systems, fully functional and DOR faces persistent road deterioration challenges on national highways and feeder roads, which is indicated by a low percentage of good condition roads during the yearly pavement inspection surveys. Road pavement maintenance planning is often reactive, based on visible surface damage assessed through the Surface Distress Index (SDI), rather than guided by long-term performance trends or exposure to potential hazards. In Nepal, no deterioration models incorporate the influence of environmental factors like monsoon rainfall, climatic conditions, geological features, and traffic factors in practice for effective road asset management.

This gap in knowledge and practice results in ad hoc maintenance decisions, inefficient use of limited budgets, and increased risk of road failures. A hazard-based deterioration modeling framework suited to Nepal's road conditions is essential for developing proactive maintenance strategies and sustaining road performance over time.

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1.3 Research Objectives

The main objective of this research is to develop a comprehensive pavement deterioration modeling framework that incorporates hazard factors, particularly monsoon rainfall which is typical in South Asia, into the assessment and prediction of road asset deterioration in Nepal. This framework aims to assist road agencies in making proactive, data-driven, and cost-effective maintenance decisions.

The specific objectives of this research are:

1. To assess the current status and challenges of road asset management systems in Nepal, including data limitations, institutional practices, and policy gaps.
2. To develop empirical hazard-based deterioration models using performance indicators (e.g., International Roughness Index, Surface Distress Index) under stochastic modeling approaches such as Markov processes.
3. To integrate rainfall as a critical environmental hazard using spatial interpolation methods (e.g., Inverse Distance Weighted, Empirical Bayesian Kriging 3D) to estimate site-specific monsoon rainfall impacts on pavement deterioration.
4. To propose a multi-dimensional continuous deterioration process model incorporating copula-based statistical frameworks that reflect the interaction between multiple deterioration indicators and hazard parameters.
5. To evaluate the proposed models' predictive capability and policy implications for enhancing maintenance prioritization and planning in Nepal's SRN.

1.4 Research Contributions

This dissertation contributes to the academic field of pavement management and provides practical value to road authorities in lower middle-income countries (LMICs) in South Asia, where climatic conditions such as monsoons significantly influence pavement deterioration.

Key contributions include:

1. A hazard-integrated deterioration modeling framework that considers both traffic and environmental factors, which is a significant advancement over traditional maintenance approach used in Nepal.
2. Incorporation of monsoon rainfall data collected by meteorological stations through advanced spatial interpolation techniques, allowing for better regional estimation of environmental hazard exposure along the road surface.
3. Development of a multi-dimensional deterioration model that captures the dependency structure among different performance indicators using copulas, enhancing the realism and accuracy of deterioration predictions.
4. Empirical validation of the models using real-world datasets from Nepal's SRN, ensuring their applicability and transferability.
5. Policy and planning recommendations for implementing data-driven RAM practices in resource-constrained settings.

The methodologies developed in this research can also serve as a template for similar regions facing comparable topographical and climatic challenges.

1.5 Structure of Dissertation

This dissertation consisted of six chapters.

Chapter 1 introduced the study's background, highlighting its significance and objectives. It also provided an overview of the thesis structure.

Chapter 2 provides an overview of Nepal's road development history, organizational structure, and current RAM practices. It highlights key institutional, financial, and technical challenges limiting the effective implementation of RAM systems.

Chapter 3 focuses on modelling pavement deterioration of Nepal's SRN using stochastic Markov hazard-based approaches. It analyses two key performance indicators: the Surface Distress Index (SDI) and International Roughness Index (IRI), to assess road conditions over time. Pavement inspection data from 2014 to 2023 are used to estimate Markov transition probabilities and hazard rates. The model outputs include expected deterioration paths and life expectancy, supporting proactive maintenance planning.

Chapter 4 integrates environmental hazard factors, particularly monsoon rainfall, into pavement deterioration modeling for Nepal's SRN. It uses geospatial interpolation techniques such as Inverse Distance Weighting (IDW) and Empirical Bayesian Kriging (EBK3D) to estimate site-specific rainfall data. The interpolated rainfall is combined with road condition data and traffic to assess its impact on pavement deterioration. A hazard-based deterioration model is developed to quantify the influence of cumulative monsoon rainfall on pavement. The results demonstrate improved prediction accuracy and support more specific maintenance strategies under varying climatic conditions.

Chapter 5 presents a continuous multi-dimensional deterioration process model that captures the interdependence among multiple pavement performance indicators using copula-based statistical methods. It incorporates surface indices such as rutting, cracking, roughness, and subsurface index represented by load-bearing capacity derived from Falling Weight Deflectometer (FWD). Joint probability density functions are developed to reflect the heterogeneity and correlation of surface and subsurface deterioration. This modelling approach enhances the accuracy of long-term pavement performance forecasting. The methodology, developed using Japanese data, can be effectively transferred to Nepal, where FWD technology has been recently introduced, to support data-driven pavement management.

Chapter 6 summarizes the research content and outcomes, aligning them with the study's objectives. It also highlighted the practical application of the study in the context of Nepal, research limitations, and future research direction to enhance the model precision and transferability.

References

[1] National Planning Commission: 16th Five Year Plan of Nepal (2024/25 to 2028/29). (2024)

[2] Shakya Manish Man, Sasai Kotaro & Kaito Kiyoyuki: Modelling Pavement Deterioration of Strategic Road Network in Nepal Based on Different Performance Indicators. Intell. Informatics Infrastructure. Vol. 4, pp. 15–26, 2023.

Chapter 2 : Institutional and Technical Framework for Road Asset Management in Nepal.

2.1 Country Overview and Organizational Context

Nepal is a beautiful country, rich in natural resources and culture in South Asia. Nepal, the landlocked, multi-ethnic, multilingual, multi-religious, mountainous nation borders India in the East, South, and West. In the north, Nepal shares a border with Xizang, the autonomous region of China known as Tibet. Well known for Lumbini, the birthplace of Buddha, the Land of Himalayas, and is the home of the tallest mountain in the world, Mt. Everest. It includes 8 of the highest 14 peaks in the world that exceed heights of 8,000 meters [1]. The capital city of Nepal is Kathmandu, which is also one of the world's oldest capitals. UNESCO has listed Kathmandu valley and Lumbini as cultural heritage sites along with Sagarmatha National Park and Chitwan National Park as Natural Heritage Sites. Kathmandu Valley has 7 UNESCO heritage sites; i) The Pashupati Nath Temple, ii) Swayambhu Nath Stupa, iii) Kathmandu Durbar Square, iv) Bhaktapur Durbar Square, v) Patan Durbar Square, vi) Boudha Nath Stupa and vii) Changu Narayan Temple in the heritage list. These sites boast cultural and historical monuments that represent various eras and regimes. Nepal rich in biodiversity and ecosystems, is also home to endangered mammals like the Bengal Tiger, One Horned Rhino, etc [2].

Geographically, it is located at 26°22'N – 30°27'N latitude and 80°04' E – 88°12' E longitude. Nepal has a land area of 147,516 sq. Km. which can be broadly divided into 3 geographic divisions; (i) Mountainous regions (15%) comprising of Himalayas and highlands, (ii) Hilly regions (68%) formed by Mahabharat, Churiya and Siwalik ranges, and (iii) Plains or Terai region (17%) are the flat river plain of the Ganges with a belt of marshy grassland, fertile cultivable land, and forests [3].

Nepal has a federal democratic republic governance system. This multi-party-political system is based on the Constitution of Nepal 2072 (2015). The head of the country is the President. Executive power is exercised by the Prime Minister and the cabinet of ministers, while legislative power is vested in the Parliament. The administrative division of Nepal comprises 7 Provinces, 77 Districts, 6 Metro Cities, 11 Sub Metro Cities, 276 Municipalities, and 460 Rural Municipalities. The people of Nepal are called Nepali or Nepalese. There are 126 Caste and Ethnic groups of people inhabiting Nepal. There are 123 languages spoken by different ethnic groups besides Nepali which is the official and national language. Nepal has its Official Calendar which is in Bikram Sambat (B.S). This calendar is approximately 56.7 years ahead of the A.D. calendar.

From the report of the recent National Census 2021, the total population of Nepal is 29,192,240. Though there is an exponential annual growth rate of 0.93%, the distribution of population is not even in all regions. 53.66% of the total population is concentrated in the Terai region, 40.25% in the Hilly region, and the Mountainous region is sparsely populated with 6.09 % of the total population. The trend of migration from rural to urban areas is significant. The census reports indicate an alarming population decrement in 32 districts compared to the last decade. Table 2.1 below shows the demographic data for the last 3 decades.

Table 2.1 Population and Household Data.

Population	**2001**	**2011**	**2021**
Nepal	23,151,423	26,494,504	29,192,480
Male	11,563,921	12,849,041	14,291,311
Female	11,587,502	13,645,463	14,901,169
Total No. of Household	4,253,220	5,423,297	6,761,059
Annual Population Growth Rate %	2.25	1.35	0.93

Source: National Census 2021.

The Constitution of Nepal has envisioned building an advanced, self-reliant, and socialism-oriented economy. The Fifteenth plan (Fiscal Year 2019/20 – 2023/24) has set a vision for achieving rapid and balanced economic development as well as prosperity, good governance, and happiness of the citizens. The Fifteenth plan has been formulated to upgrade Nepal from a least developed country to a developing country and achieve the targets of SDGs by 2030 to uplift Nepal to the level of a middle-income country through an increase in income level, development in infrastructure, and the reduction of economic risks.

In harmony with international commitments, Nepal needs to achieve the SDG goals by 2030. The SDG goals are being incorporated into the development programs of all three levels of government. The recent value for some of the key indicators of SDGs is presented in Table 2.2 which indicates improvement in the country's socio-economic condition [4].

Table 2.2 SDG Goals, Key Indicators, and Recent Value.

S.No	SDG Goals	Indicator	Recent Value
1	No Poverty	Population under Poverty Line	25.2%
2	Zero Hunger	Prevalence of undernourishment	5%
3	Good Health and Well Being	Mortality rate under 5 (per 1000)	28
4	Quality Education	Youth Literacy Rate	92%
5	Gender Equality	Women Business and the Law Index Score	80.6
6	Clean Water & Sanitation	Population using basic drinking water	90%
7	Affordable and Clean Energy	Access to Electricity	89.9%
8	Decent Work and Economic Growth	GDP Growth	4.2%

9	Industry, Innovation, and Infrastructure	Manufacturing, Value Added (% of GDP)	5
10	Reduced Inequalities	The average transaction cost of sending remittance to a specific country	4.54
11	Sustainable Cities and Communities	Urban Population growth rate	3.9%
12	Responsible Consumption and Production	Total Natural Resources Rents	0.5%
13	Climate Action	Total Greenhouse gas emission	44,200
14	Life Below Water	Total fisheries production	81,070 Mt
15	Life on Land	Forest Area Percentage	41.6
16	Peace Justice and a Strong Institution	Completeness of Birth Registration	77
17	Partnerships for the Goals	Access to Internet	65.9%

Source: data.worldbank.org/country/np

2.2 History of Road Development in Nepal

The first motorable road in Nepal was constructed in the Kathmandu valley in 1924. The total road length in Nepal was 376 Km until 1950. Nepal is a landlocked country, road transportation is the primary means of transport for trade and services. The economic development of the country linking the capital city by means of the road with the neighboring country India in the south was started in 1953 by the construction of Single Lane macadam roads from Bhimphedi to Amlekhgunj and Butwal to Bhairahawa. Similarly, the construction of roads from Kathmandu - Kodari to the northern border with China was started in 1956. The development of road networks has always been the priority since the beginning of planned development programs in 1956. In 1964 Government of Nepal initiated the construction of East West Highway which is a 1028 Km long main arterial

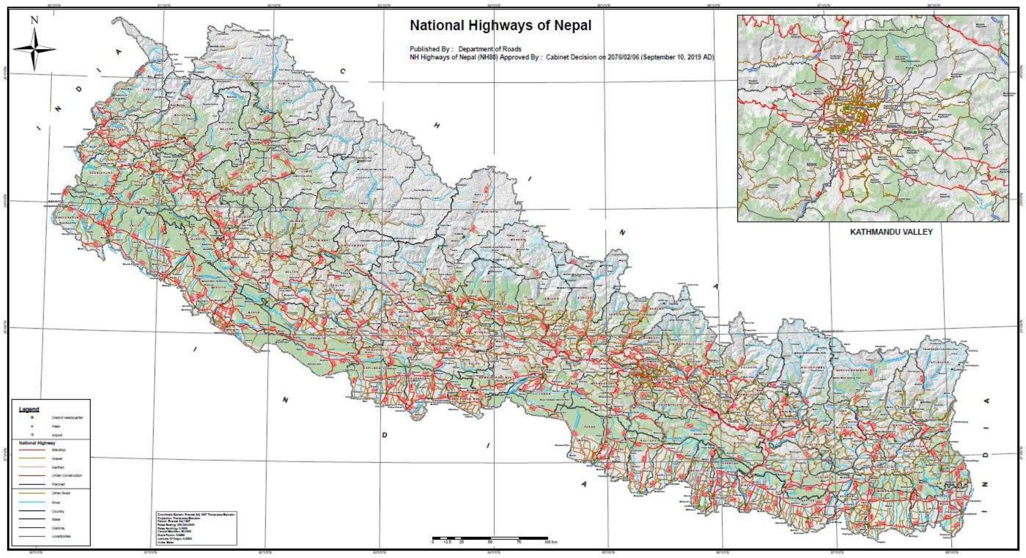

Figure 2.1 Strategic Road Network of Nepal..

route running longitudinally through the country with the support of bilateral and multilateral agencies. The first long-term road development plan was formulated with the involvement of several advisors in 1968. Since 1976 Strategic Road Network (SRN) is developing in the country. At Present Nepal has 33,716 Km of road network constructed and maintained by various road agencies like the Department of Roads (DOR), Department of Local Infrastructure (DOLI), Department of Urban Development and Building Construction (DUDBC), Municipalities, etc. Out of 77 district headquarters, 1 district headquarters Simikot of Humla District is remaining to be connected by Strategic Road Network to date [5]. The map showing the Strategic Road Network (SRN) under MOPIT is presented in Figure 2.1. SRN network includes National Highway, Feeder Roads, and Sub Urban Road Network.

The Government of Nepal constitutes 21 Ministries, 28 Departments, and 9 Constitutional Bodies. The Ministry of Physical Infrastructure and Transport (MOPIT) is the central authority responsible for infrastructure planning and development relating to the transport sector to enhance the economic and social development of the country. The following are the departments and institutes under MOPIT involved in RAM.

1. Department of Roads
2. Department of Transport Management
3. Department of Railways
4. Road Board Nepal
5. Nepal Engineering Council

MOPIT was established to bring important transport infrastructure development agencies under the common ministry. The main aim of this organization is to harmonize the policies and bring efficiencies and effectiveness in the provision of infrastructural services guided by the National Transport Policy,2001 that aims to contribute to the development of the overall economic, social, cultural, tourism, etc. sectors of Nepal by developing a sustainable, reliable, low cost, safe, convenient, and self-sufficient transport system. For attaining the goal, the Road Network is classified as follows based on National Transport Policy,2001.

1. Strategic Road Network
   1.1. National Highway
   1.2. Feeder Road
   1.3. Special Purpose Road
2. Local Road Network
   2.1. District Roads
   2.2. Rural Road
   2.3. Agricultural Road
   2.4. Main Trail
   2.5. Local Trail
3. Urban Road Network

National Transport Policy,2001 also defines the responsibility for construction and maintenance of Strategic Road Networks by central government agencies and Local Road Networks by the local agencies. MOPIT which is the government agency whose main purpose is to translate government policies for the road sub-sector into the provision of services was separated from Public Work Directive and established in 1970 A.D[6]. Before DOR, the Road Transport Office (RTO) was formed for road works consisting of engineers from Nepal, India, and the USA which was later merged into DOR. DOR is a service- oriented institution with a vision of "Managing Roads for National Integration and Socio-Economic Development". DOR aims to provide efficient and effective service to all road

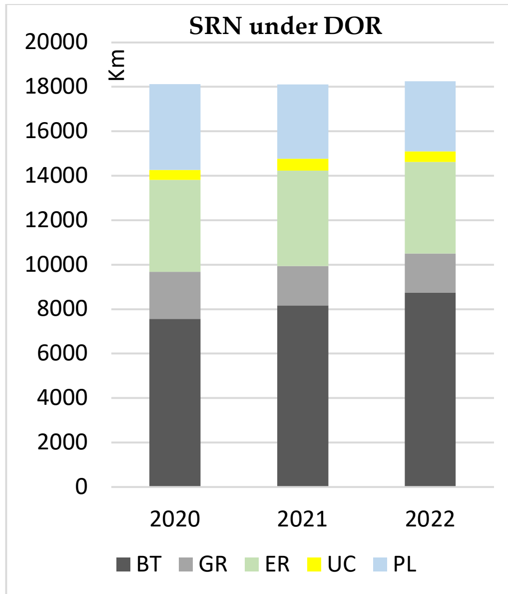

Figure 2.2 SRN pavement type.

users as per the clearly defined end goal of the department – "the reduction of total road transport costs". This departmental end goal was also incorporated by NPC into the 8th National Plan (1991/92). The total road transport costs are the sum of the interdependent costs of road construction, road maintenance, and vehicle operating costs. [7].

At Present, the total length of SRN is 14,618 Km. This excludes the under-construction and planned highway of approximately 3,635 Km. The cabinet of Nepal approved 80 National Highways with a total network length of 14,913 Km on 2019 September 10 which also includes 1,324 Km of the Asian Highway Network. In the road network, there is approximately a total of 3,300 numbers of SRN and LRN Bridges. The responsibility for the construction of both SRN and LRN motorable bridges is undertaken by DOR. In the previous fiscal year 2078/79 (2021/22), the construction of 282 numbers of bridges has been completed. For the fiscal year 2079/80 (2022/23), there are approximately 133 SRN Bridges and 424 LRN Bridges

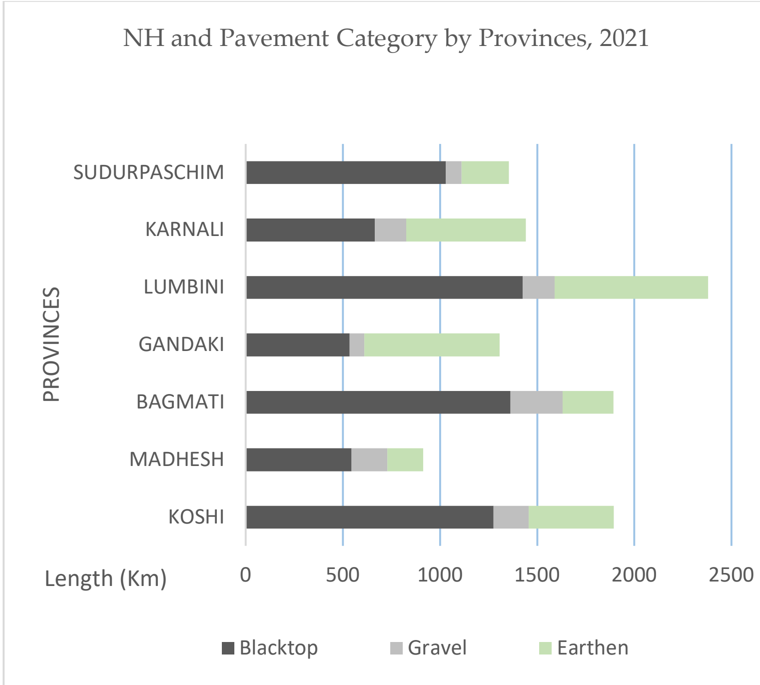

Figure 2.3 NH & Pavement Category by Provinces,2021.

are under construction. Similarly, around 745 major and minor bridges are under the planning and designing phase [8]. The total road length of the national highway for the last 3 years and the Pavement Category by Provinces are presented in Figure 2.2 and Figure 2.3.

2.3 Department of Road

Department of Road (DOR) Strategy, July 1995 highlights the departmental policy document that was developed with the strategies to attain the end goal - "the reduction of total road transport cost". The strategy was developed using the principles of Policy Action Planning and is composed of 6 objectives, 9 policy options, and 51 Key measures. The objectives are the combination of interrelated targets which when taken together should enable the Department to realize the end goal. The Policy

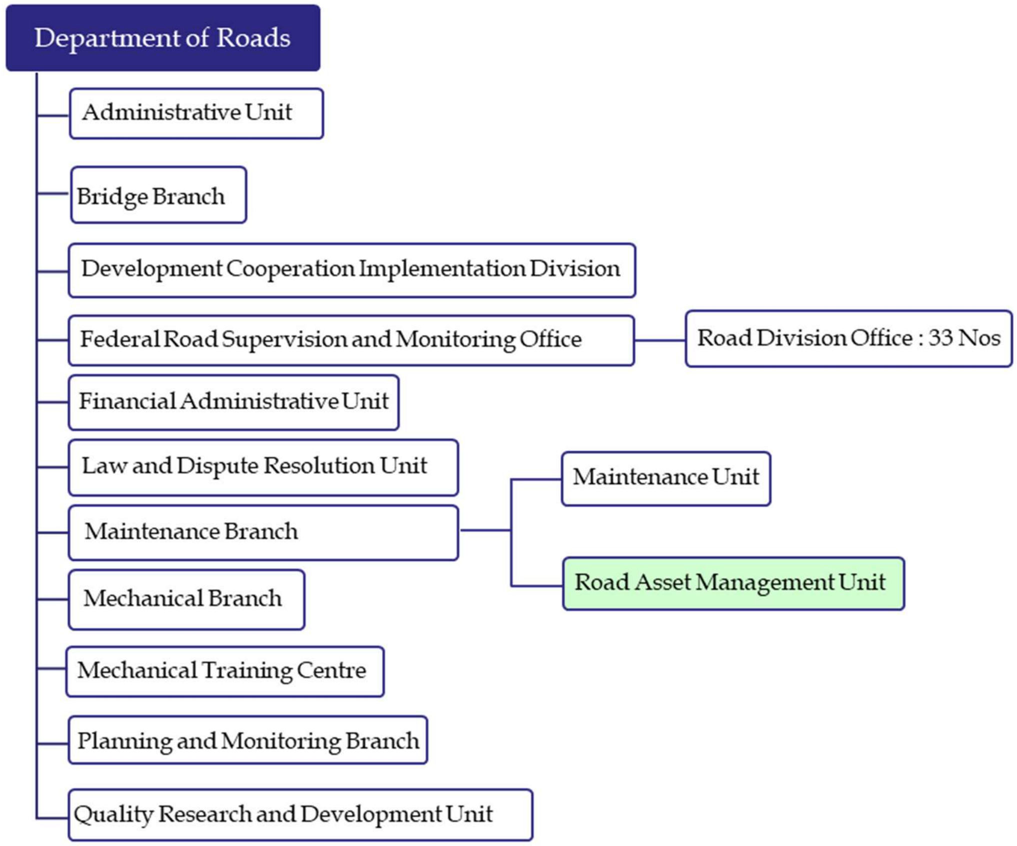

Figure 2.4 Organization Structure of the Department of Roads

Options represent a range of feasible policies through which the Objectives can be achieved. Similarly, the 51 Key Measures comprise a series of activities designed to translate the Policy Options into practice and hence generate the conditions necessary for realizing the Objectives.

The Objectives, Policy Options, and Key Measures together comprise the DOR Strategy [7].

2.4 Road Board Nepal (RBN)

Roads Board Nepal was established under the Roads Board Act 2058 (2002). This is an autonomous organization based on Public Private Partnership (PPP) Model. RBN aims to provide sustainable funds for planned maintenance of the roads as envisioned by National Transport Policy, 2001. The road board fund is composed of direct road toll collected from the road user, fuel levy, and vehicle registration fee. The main function of RBN is to collect, manage and allocate funds for road maintenance activities to the Road Agencies (RA) annually. The DOR is identified as the key RA for the maintenance of SRN. Similarly, the Maintenance of urban, district, and local roads is governed through the Department of Local Infrastructure Development (DOLI) in coordination with the District Coordination Committees (DDC) and Municipalities (MC) jointly recognized as the road agency for LRN.

Standards, Manuals, Guidelines, Checklists, etc used in RAMS

1. Definition of Maintenance and Maintenance Activities, November 1994
2. Departmental Policy Document, The DOR Strategy, July 1995
3. DOR Pavement Design Guidelines, 2014
4. Guidelines for Inspection and Monitoring of Bridges, Vol 1&2, 2013
5. National Transport Policy, 2001
6. Nepal Road Standard 2070
7. Road Pavement Management, MRCU 1995
8. Standard Procedure for Periodic Maintenance Planning, November 2005
9. Web Based Systems such as ARMP, BMS, BSMS, RIDMS, etc.

2.5 Status and Evolution of RAM Systems within DOR

In the past, the Highway Design and Maintenance Standards Model (HDM-III), developed by the World Bank, has been used for over two decades for technical and economic appraisals of road investment projects. An international study group sponsored by UK Department for International Development (DFID), the World Bank (IBRD), the Asian

Development Bank (ADB), and the Swedish National Roads Administration (SNRA) was set up in August 1993 prepared a successor to HDM-III as HDM-4 (Highway Development and Management Model). At present both these tools are not functional.

The Highway Management Information System (HMIS) unit under Planning Branch within DOR has a Geographical Information System (GIS) based road inventory data with 25 parameters under its jurisdiction. Under the funding of RBN, HMIS has been collecting of International Roughness Index (IRI), Surface Distress Index (SDI), and Annual Average Daily Traffic (AADT) on yearly basis. Based on the data, the simple empirical method developed about 25 years back is still being used to prepare the Annual Road Maintenance Plan (ARMP) for all Roads Division Offices (RDOs). DOR engineering staffs are familiar to some extent with using a cloud-based database. The Bridge Management System (BMS) for managing bridge inventory and a smartphone application-based Bridge Site Monitoring System (BSMS) is already in use for some years [9].

The modern Road Inventory Management System (RMIS) with GIS interface is recently under development by Planning Branch, HMIS Unit, and DOR and hasn't been linked to the maintenance planning. Thus, it can be inferred that the importance of RAMS has been considered by DOR from the beginning and concepts have been acquired to preserve and maximize the service period of the road asset.

DOR under the funding of Strategic Roads Connectivity and Trade Improvement Project (SRCTIP) is planning to establish a web-based RAMS to provide real-time data on road features as well as on maintenance history, surface condition, traffic volume, active landslides, cross-drainage structures, road accidents, etc. Through integration with other systems, the analysis of the data will help to make the best possible decisions for road maintenance, safety, and management. This will further develop RAMS and help establish fully functional RAMS in DOR.

2.6 Performance Measure, Level of Service, and Forecasting

2.6.1 Performance Measure

Road Asset deteriorates over time irrespective of the design and construction standards that have been adopted. The deterioration is a progressive process and is influenced by several factors that are grouped under three main headings:

1. Environmental Factors such as terrain, climate, and local practices
2. Traffic Conditions such as Traffic Volume and Axle Load
3. Construction Factors relating to design and construction standards, quality of materials, and workmanship.

The performance measure is the starting point for pavement management to understand the characteristics of pavement deterioration and to determine the pavement condition. This provides knowledge about the nature and extent of the problem to be addressed. The performance measures for unpaved (earthen and gravel roads) and paved (bituminous roads) are different.

Unpaved Roads: The action of traffic causes corrugations and rutting. During the monsoon, the damages are accelerated with deep ruts, gullies, and washouts. Surface roughness is considered the main performance measure for unpaved roads. Maintenance activities such as grading the pavement surface and re-graveling works are planned to keep the road in serviceable condition. It is estimated that with routine drainage maintenance only, the expected life for unpaved roads in Nepal is not more than 3 years (two monsoons) [10].

Paved Roads: DOR considers the following primary measures of pavement to determine how well the pavement is performing and meets the serviceability requirement of the road.

1. **Surface Roughness**: Surface Roughness is closely related to the pavement condition and the VOC increases with an increase in the

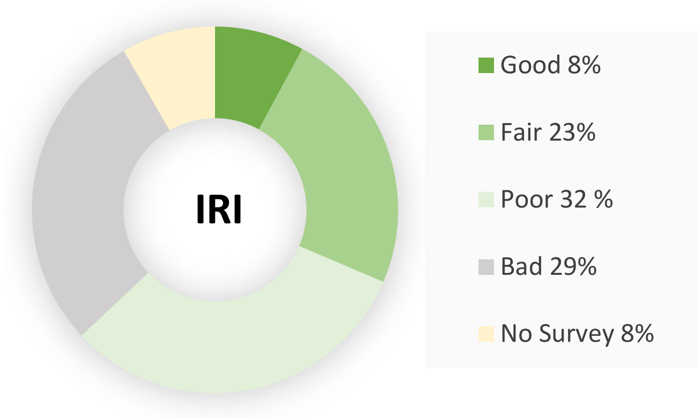

Figure 2.5 Road Condition, IRI, 2022.

roughness of the road. International Roughness Index (IRI) expressed in m/Km is used to provide a common scale for recording road roughness. The DOR Planning Branch has been conducting the annual surveys of SRN from FY 1992/93 and the records as held on the HMIS central database. DOR Planning Branch uses a vehicle-mounted Bump Integrator which is a response-type instrument to measure the surface roughness annually.

Table 2.3 Road Condition based on IRI (Paved Roads only)

Condition	IRI m/Km
Good	<4
Fair	4-6
Poor	6-8
Bad	>8

Source SWRP & PIP report 2007.

2. **Surface Distress**: Surface Distress provides a visual indication of pavement deterioration. The method adopted by DOR is a simplified procedure recommended by the World Bank which has been modified to suit the conditions in Nepal and the need for DOR. Pavement distress

surveys are carried out manually in the DOR by trained Highway Engineers working as a two-person team; this method in use is a drive-and-walk survey. Surface distress comprises cracking, disintegration (potholes), deformation, texture deficiency, pavement edge defaults, and

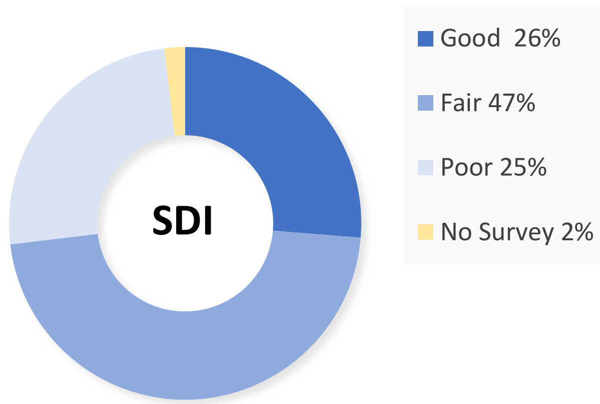

Figure 2.6 Road Condition, SDI. 2022.

maintenance works (patching) These faults are visually assessed using a 10% sampling procedure and recorded using a cumulative index called Surface Distress Index (SDI).

Table 2.4 Road Condition based on SDI (Paved Roads only)

Condition	SDI
Good	0.0 - 1.7
Fair	1.8 - 3.0
Poor	3.1 - 5.0

Source Road Pavement Management, MRCU,1995

SDI is a six-level rating index from 0-5. A rating of 0 indicates the pavement surface without any defects, whereas a rating of 5 indicates the maximum possible deterioration. DOR plans to conduct surveys for surface distress of all the SRNs annually. DOR has been carrying out pavement distress surveys on the SRN since 1993/94 and the records as held on the HMIS central database [10]. The following road condition is suggested based on averaged SDI value for each road link for Nepal in Table 2.4.

3. **Structural Capacity**: The structural capacity of a pavement is the measure of a pavement's ability to carry the design loading. The Structural Number (SN) is related to the California Bearing Ration (CBR) and the thickness of the individual pavement layers. Pavement deflection is also the normal measure of pavement strength. The use of Benkelman Beam for measuring the deflection in conjunction with Dynamic Cone Penetration for determining the in-situ CBR values of pavement layers is used by DOR at the Project Level to determine the Structural Capacity of a pavement. Only project-specific records of Structural Capacity are available. Recently DOR purchased Falling Weight Deflectometer to determine the Structural Capacity of the road network.
4. **Pavement Texture**: The measurement of pavement texture or friction is principally concerned with safety on paved roads. The road pavement surface loses its texture under the action of traffic and climate resulting in a reduction in skid resistance. The ability of pavement to provide skid resistance is measured in terms of a Sideways Force Coefficient (SFC) and Sensor Measured Texture Depth (SMTD). No surveys are conducted for determining SFC and SMTD in DOR. For current practice, DOR Standard Specification for Road and Bridges recommends that aggregates with high polished stone value be used in the wearing course, conduct timely resealing works of good quality and provide adequate camber to the pavement to ensure good pavement texture.

2.6.2 Level of Service

Level of service (LOS) is a term used to qualitatively describe the operating conditions of a roadway based on factors such as speed, travel time, manoeuvrability, delay, and safety. Among six Levels of Services (LOS) viz. "A" to "F". Nepal Road Standard,2070 (2013), recommends adopting a LOS "B" for the design capacity of roads. Under this condition, traffic will experience congestion and inconvenience during some of the peak hours, which may be acceptable [11].

For the SRN under operation, a significant loss in serviceability causes discomfort to road users, and increases the travel time which further increases the total road transport cost. The objective of DOR is to improve the maintenance operation considering the policy option for improved periodic maintenance of SRN such that the road agency can provide a reasonable level of service to the road user at the lowest life cycle cost. For maintenance of the SRN, based on the SDI value Planned Maintenance is recommended on roads in good/fair condition and rehabilitation/reconstruction is generally needed for roads in poor condition to bring them to a maintainable state.

Therefore, the discounted cost can be expressed by equation (2.1) as follows

$$M_c = VOC_1 - VOC_2 \tag{2.1}$$

Where,

M_c = the discounted costs per km of the measure adopted to provide a serviceable road over time “t”.

VOC_1= the discounted VOC per km on the road over the time “t” without the measures.

VOC_2 = the discounted VOC per km on the road over the time “t” with the measures.

2.6.3 Forecasting

The rate of deterioration of the road pavement is important for planning the appropriate maintenance approach. However, the pavement deterioration curve for the condition of Nepal is not available to forecast future deterioration. An intervention approach using economic models such as HDM is not approved for implementation with the present road network and traffic levels [10].

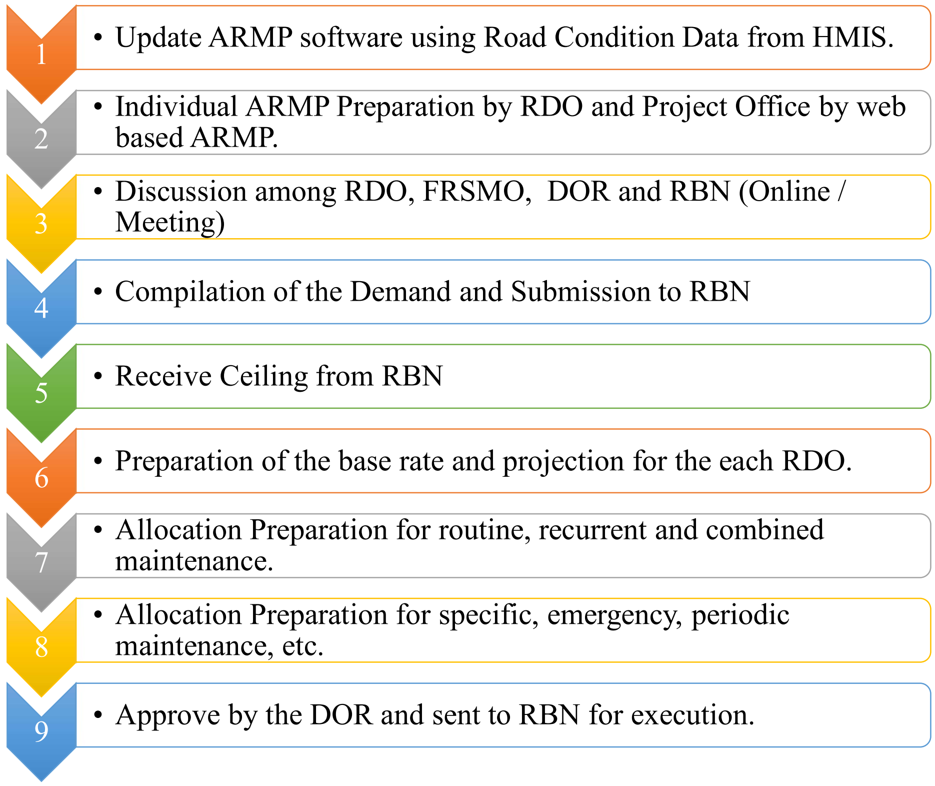

Figure 2.7 Annual Road Maintenance Planning

The DOR developed a strategy in 1995 for road maintenance. Based on this strategy, Planned Maintenance has been implemented by DOR since 1995 for periodic maintenance comprising cyclic resealing of paved roads at the divisional and regional levels. The main aim of planned maintenance is to keep existing maintainable roads in serviceable condition (good/fair, SDI range 0.0 – 3.0), reduce vehicle operating costs, and provide more comfort to road users. The management procedures and planning guidelines for periodic maintenance were developed under the Strengthened Maintenance Divisions Programme and are based upon the current DOR Policy. The recommended resealing interval is 5 to 8 years depending upon the environmental and traffic conditions. This method considers prioritizing in selecting the road using 4 parameters [12].

1. Road Age
2. Visual Survey rating
3. Traffic

4. Strategic Importance

The cyclic method for determining road maintenance priorities has so far proved popular with the Department engineering staff, as they can readily see for themselves what the problems are instead of relying upon planning specialists at the central level. A web-based Annual Road Maintenance Programme (ARMP) Software is developed, and all levels of maintenance staff are fully involved in the planning process, from the consultants who collect field data and update the road register, Divisional Engineers who prepare their priority list, Superintending Engineers who screen out the roads unsuitable for resealing and rank roads at a regional level, through to DOR central office who summarize the data to produce a national Integrated Annual Road Maintenance Plan for submission to the Road Board for allocating the next fiscal year maintenance budget.

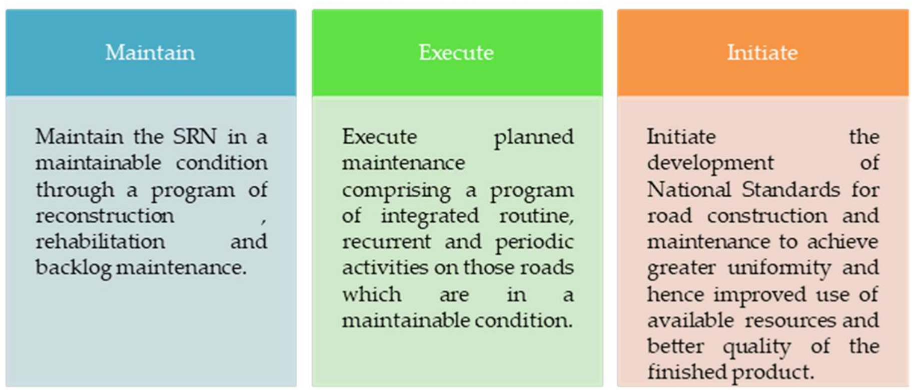

Figure 2.8 Maintenance Strategy of DOR

2.7 Maintenance Strategy and Operation

Maintenance of the Strategic Road Network is the prime responsibility of the Department of Roads. The DOR is headed by a Director General assisted by 5 Deputy Directors General (DDG), one of whom is responsible for maintenance. There are 4 Federal Road Supervision and

Figure 2.9 DOR Maintenance Policy

Monitoring Offices led by 4 Superintending Engineers who as the connecting link between Head Office at Kathmandu and the Road Division Offices (at present 33 RDO and SD, DSB Project Office, JICA) [13].

The objective of maintenance activity is to provide cost-effective safe roads for users. There are four types of maintenance activities.

1. On Road maintenance
2. Roadside support maintenance
3. Emergency maintenance
4. Bridges maintenance

Each of the activities is referred to the four sub-types they are: routine, recurrent, periodic & preventive.

1. Routine maintenance is the daily activities required continually on every road because of environmental degradation, irrespective of its engineering characteristic or traffic volume
2. Recurrent maintenance, required only at intervals during the year with a frequency that depends mostly on the volume of traffic using the road
3. Periodic maintenance, required only certain intervals,
4. Preventive maintenance, is required to adapt the road to the changing nature of the slopes and streams (i.e. to the geophysical environment)

The condition of the road and indication of the type of treatment needed, based on the defined range of SDI, is given in the following Table 2.5.

The condition of the road and indication of the type of treatment needed, based on the defined range of SDI, is given in the following Table 2.5.

Table 2.5 Type of Treatment based on SDI

SDI Range	Condition	Type of Treatment
0.0 - 1.7	Good	Routine and Recurrent Maintenance
1.8 - 3.0	Fair	Routine and Recurrent + Periodic Maintenance
3.1 - 5.0	Poor	Backlog Maintenance, Rehabilitation, or Reconstruction

Source: Road Pavement Management, MRCU,1995

2.8 Road Asset Management Philosophy

The RAM philosophy is represented by equation (1). MC << (VOC1 – VOC 2) . The following are the three strategies considered for planning and executing maintenance activities [10].

Strategy 1: Periodic maintenance comprising interdependent routine, recurrent and periodic maintenance activities by deferring the need for the most costly activities of rehabilitation and reconstruction and by keeping vehicle operation costs to a minimum. Planned maintenance can be considered the optimal strategy in purely economic terms. This strategy is only applicable effectively to roads in a maintainable (good/fair, SDI range 0.0 – 3.0) condition. The detailed methodology for the selection of the roads is explained in Standard Procedure for Periodic Maintenance Planning, November 2005.

Strategy 2: The provision of minimal ad-hoc routine and recurrent maintenance activities followed by rehabilitation of the pavement when it reaches poor condition. As the annualized cost of rehabilitation is three to four times the cost of the foregone maintenance, this is not an effective strategy. This does not take into account the higher VOC due to the resulting increase in pavement roughness. Depending on the present limit on DOR capacity and maintenance funding, it can be assumed that DOR cannot implement planned maintenance on the whole of the strategic

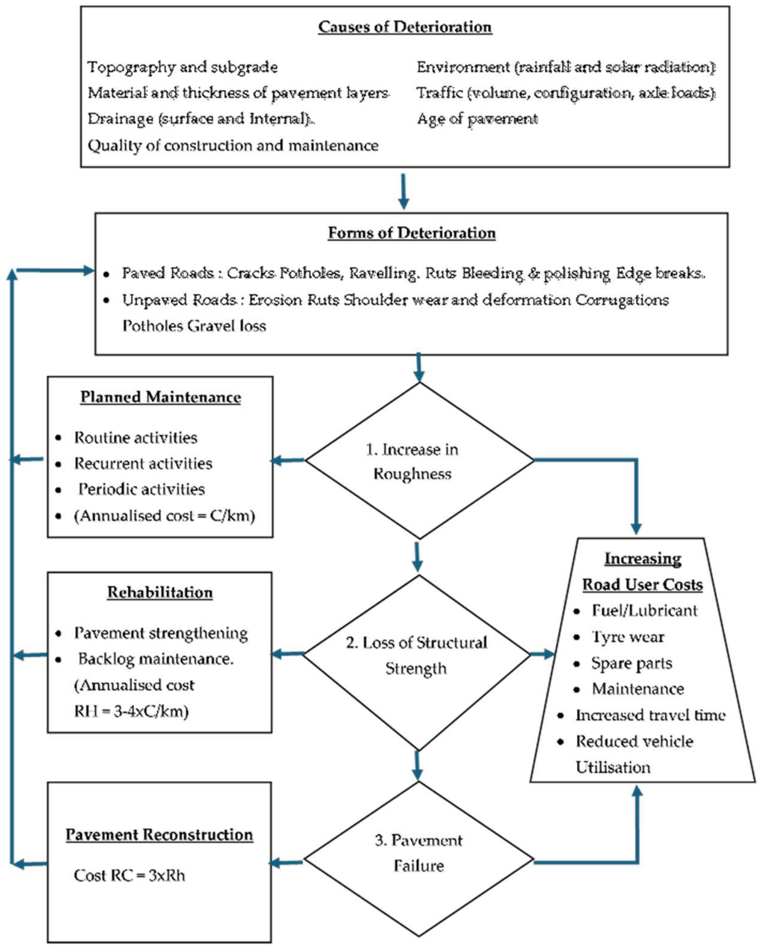

Figure 2.10 Road Pavement Deterioration and Treatment Cycle

network. While the aim of DOR should be to move from the present application of Strategy (ii) to Strategy (i) gradually.

Strategy 3: The provision of minimal routine and recurrent maintenance activities only until such time as the road becomes totally unserviceable and full pavement reconstruction is necessary. As the cost of reconstruction is three times the cost of rehabilitation, this strategy is extremely costly for all roads except for those with minimal traffic.

2.9 Funding Sources and Budget

Road maintenance activities are funded through the budget allocated to maintenance by the Ministry of Finance. There are two budgets covering maintenance: Road Board Nepal Fund and Foreign Partners.

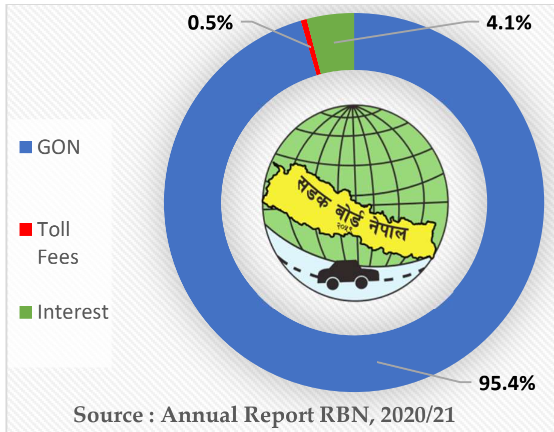

Figure 2.11 RBN Fund Sources

1. Road Board Nepal Fund is the funds for planned maintenance as described in the previous section. The total fund collected by RBN for the fiscal year 2020/21 is NRs. 7.37 Billion. RBN has currently been availing the following resources:
1. Fuel levy on diesel and petrol
2. Vehicle registration fees
3. Road user charges (Toll Fees)
4. Interest from Funds etc.

2. Foreign Partners: It is well accepted that reconstruction and rehabilitation works are not included in Planned Maintenance. These road maintenance activities require huge capital reinvestment, and these activities are funded by donor funds. Some of the examples of these projects are : (a) SRCTIP which supports Periodic Maintenance of 3400 Lane- Km of high traffic Core Road Network. This aims to maintain more than 80% of` CRN in Good Condition at the end of the project period. CRN is the road section with traffic < 2000 PCU (excl.

motorcycles and non-motorized vehicles). The estimate for this project is 80 Million USD for 5 years of which 70% is IDA Loan and 30% by GON. The annual cost will be 16 Million USD for periodic maintenance of 680 Lane- Km of CRN.

Similarly, Millennium Challenge Account Nepal is the U.S. Government's Millennium Challenge Corporation (MCC) compact with the Government of Nepal. It includes 305 km of Road Maintenance Project Components with an estimated cost of 52.3 million USD including Training and Capacity Strengthening for the DOR and RBN to improve administration and Maintenance.

Maintenance Schemes

There are various methods for undertaking maintenance activities depending on the nature, scale, and urgency of the work. Routine maintenance work is the most important activity among all maintenance activities as it includes the preservation of the drainage system which is the critical element of the road. Generally, these works are labor-based works and DOR has adopted the length worker and supervisor system developed by SMD Programme for executing the routine maintenance works in all RDO [14]. Besides the routine maintenance works other small-scale preventive maintenance works and emergency maintenance works especially during the critical period (monsoon) are done departmentally or direct contracting by Road Divisional Offices. These activities include reasonable measures necessary to clear the road closure or blockage, protect the road from further deterioration and reinstate the road in serviceable condition. Heavy Equipment Divisions (HED) provide heavy equipment to RDO offices for emergency maintenance work and quick response.

The other maintenance works relating to specific and periodic maintenance are estimated and procured by the respective RDO. The competitive bidding procedure is in accordance with Public Procurement Act and Public Procurement Regulations. The maintenance contract is awarded to the eligible contractor. The contract administration is

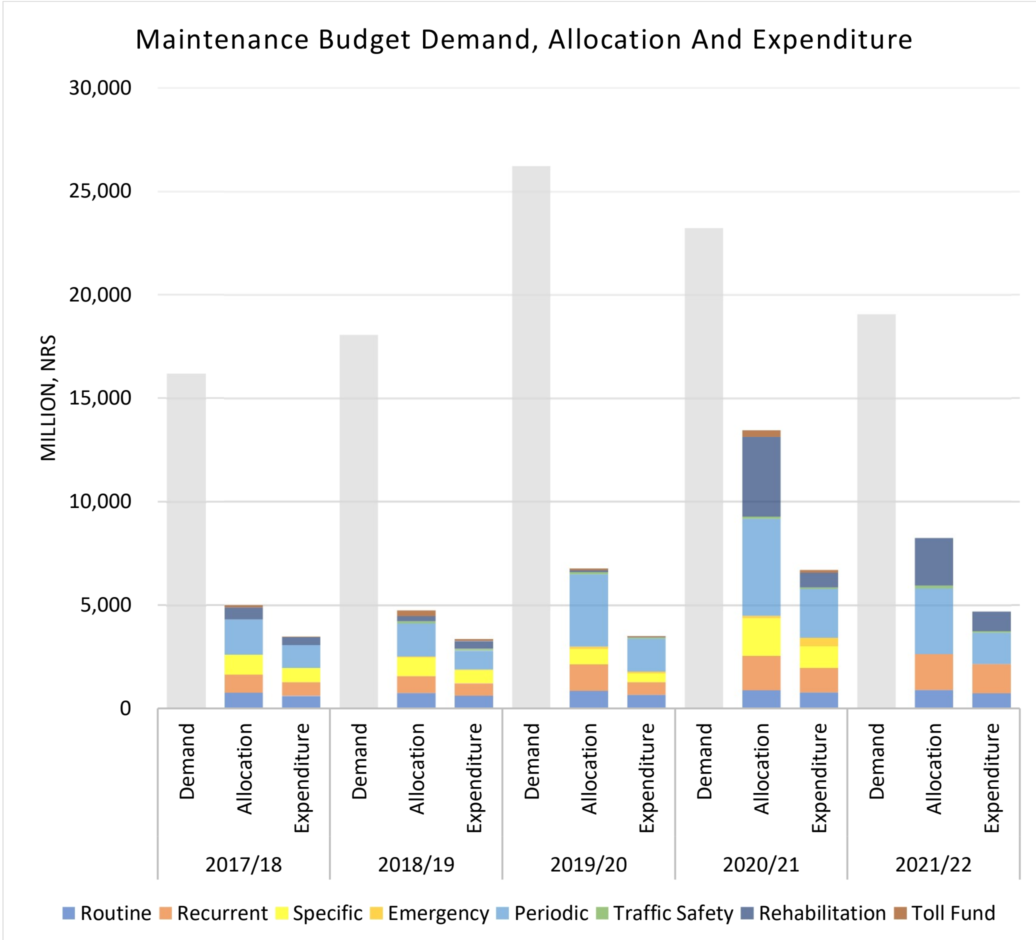

Figure 2.12 Maintenance Budget

performed by the corresponding RDO and the monitoring & evaluation are done by Superintending Engineers of Federal Highway Supervision and Monitoring Offices and RBN.

The scenario of budget demand of DOR, allocation by RBN, and expenditure on highway maintenance for the past 5 years are presented in Figure 2.6. It is noted that there is 100% allocation for Routine and Recurrent maintenance activities. The average allocation for the last 5 years is 37.11 % and the actual highway maintenance cost is 21.10 % which is very low compared to initial demand.

2.10 Way Forwards

The knowledge of the deterioration of the road pavement is important for determining the timing of remedial actions. However in the absence of a pavement deterioration model for Nepal, it is very difficult to forecast future conditions, have a strategic maintenance plan, and optimize the maintenance cost.

The current DOR Policy and Practice to resurface the roads at a fixed interval of 5-8 year interval depending upon surface distress, environment, and traffic conditions only are to be reviewed and refined considering the parameters such as pavement structural capacity and surface texture for different surface types of pavement. This review should also consider the historical data and specific experience gained by road engineers throughout Nepal.

Referring to Chart 4, there is a prime necessity to establish robust RAMS to keep a balance between unrealistic high maintenance demand, low allocation, even low absorption capacity, and the deteriorating condition of SRN shortening the service life of the road asset.

Budget deficiency cannot always be the prime reason for poor road conditions. The Integrated Annual Road Maintenance Program,2022/23 has estimated NRs 8.2 billion for maintenance of SRN in this fiscal year. The allocation is NRs 7.92 billion which is approximately 96 % of the total demand. This is a satisfactory allocation compared to the past average allocation of around 37% of the total road maintenance demand. With the sufficiency in allocation and proper implementation of maintenance strategy, a positive result in improvement of road condition is expected in the future.

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Chapter 3 : Modelling Pavement Deterioration of Strategic Road Network in Nepal Based on Different Performance Indicators

3.1 Introduction

Road asset management (RAM) is a type of social infrastructure asset management that is applied to road assets, such as roads, bridges, and other road components. The main purpose of this concept is to implement a strategic management plan to minimize the life cycle cost of road assets through the action of regular inspection, degradation forecast, and implementation of suitable repair activities at the best time.

The implementation of RAM in Nepal can be traced to the Rana Regime (1846-1951). The road office named '*Bato Kaj Goshwara*' for road construction and '*Chhembhadel Adda*' for maintenance works was established which was later transformed into public work directive after the advent of democracy in 1951. Department of Roads (DOR) was separated from the public work directive in 1962 and established as a service-oriented institution responsible for the construction and maintenance of Strategic Road Networks (SRNs) in Nepal[3].

At present Nepal has 33,716 Km of road network constructed and maintained by various road agencies (RA) like the DOR, Department of Local Infrastructure (DOLI), Department of Urban Development and Building Construction (DUDBC), municipalities, etc[4]. The DOR is identified as the key RA for the construction and maintenance of SRN. SRN includes the National Highway, Feeder Roads, and Sub Urban Road Network of a total length of 14,656 km and 1,656 numbers of bridges excluding the under-construction and planned highway of approximately 3,536 km[5,6]. DOR Strategy, July 1995 highlights the departmental policy document that was developed with the strategies to attain the end goal -

"the reduction of total road transport cost". This departmental end goal was also incorporated by the National Planning Commission (NPC) into the 8^{th} National Plan (1991/92). The total road transport costs are the sum of independent costs of road construction, road maintenance, and vehicle operating costs[7]. The comprehensive guideline of maintenance activities adopted by DOR to preserve the road in a serviceable state for road users and defer the need for high-cost road maintenance activities are well described in policy documents[8].

The annual budget for SRN maintenance is allocated by the Roads Board Nepal (RBN). The road board fund is composed of direct road toll collected from the road user, fuel levy, and vehicle registration fee[9]. There are four major performance measurements: i) surface roughness ii) surface distress iii) structural capacity and iv) pavement texture are suggested to determine how well the pavement is performing and meeting the serviceability of the road[10].

Under the funding of RBN, the DOR has been collecting inspection data for International Roughness Index (IRI), Surface Distress Index (SDI), and Annual Average Daily Traffic (AADT) yearly. The traffic Survey involved traffic counting and analysis from 160 stations which are at the major nodal locations on the strategic road network of Nepal. Based on these data, the simple empirical method developed in 2005 is used to prepare the integrated annual road maintenance plan for all road division offices[11]. The Planned maintenance and the detailed methodology for the selection of the roads are explained in "Standard Procedure for Periodic Maintenance Planning", published in November 2005 in which the key pavement performance parameter considered is SDI[11]. The annual road condition survey conducted for SDI in 2023 indicates 58.4 percent of the bituminous roads are in fair to good condition (SDI range 0.0-3.0)[5].

SDI is a measurement of pavement distress such as cracks, potholes, rutting and other forms of pavement deterioration. Highway engineers and pavement experts conduct visual surveys and record the severity of the distress. This data is used to calculate the SDI value for the surveyed road section. The methodology and interpretation of the results may vary depending on the surveyors and the guidelines of the road agencies. In context of Nepal, SDI surveys are done manually by trained highway engineers. Pavement surface distress is visually assessed by using a 10% sampling procedure and recorded. SDI is expressed in rating scale from 0 to 5. The rating 0 indicates a pavement surface without any defects, whereas a rating of 5 indicates the maximum possible deterioration. This method adopted by DOR is a simplified procedure recommended by the World Bank which has been modified to suit the conditions in Nepal and the need for DOR. Detail procedure for the determination of SDI value for each road link is described in "Road Pavement Management, MRCU"[10].

On the other hand, IRI is an internationally recognized standard for assessing road roughness. It is expressed in m/km. The standard procedure and roughness measuring devices are standardized by World Bank sponsored International Road Roughness Experiments (IRRE) conducted in Brazil in 1982[12]. The results are consistent and can be compared with other road sections locally and globally. The results of IRI can be correlated with ride quality and road user satisfaction.

DOR is facing the challenge of achieving one of its important maintenance policies to maintain over 95 percent of SRN in fair to good condition. In the future aging road infrastructure and an increase in traffic volume will add up more difficulties to achieving this target. Timely predictions on maintenance demands of the road assets in the future along with the appropriate financial plans to implement the optimal repair strategy are important to overcome this challenge. In addition, the rate of deterioration of the road pavement is important for planning the appropriate maintenance approach. However, the pavement deterioration curve for the condition of Nepal is not available to forecast future deterioration.

In this study, the Markov deterioration hazard model is applied for deterioration forecasting of SRN using road condition data set from 2014 to 2023 using two different performance parameters, SDI and IRI. The deterioration model can be applied to estimate the hazard rates and residual life of the pavement. Further, the average Markov transition probabilities (MTP) matrix, the hazard rate for each transition state, the life expectancy, and the expected deterioration path describing the average deterioration process during the life expectancy rating is presented in this paper.

3.2 Methodology

To forecast the deterioration progress of the pavement a statistical deterioration model based on past inspection results is applied. The Markov deterioration hazard model is a statistical model used to forecast the deterioration progress of pavement developed by Tsuda et al., 2006[13]. In this model, a rank order is assigned as a condition state depending on the result of the past inspection data. The Markov transition probabilities are estimated to represent the deterioration progress between the condition states. This model is widely preferred for sound maintenance strategies and budget management policies. In this paper, the application of the Markov deterioration hazard model for deterioration forecasting of SRN in Nepal using the SDI and IRI data set from 2014 to 2023 is presented.

The road condition data for the study is acquired from Highway Management Information System Unit (HMIS) under Planning Branch within DOR. The road condition data is acquired from the annual road inventory data recorded in the road register of SRN from 2014 to 2023. The rainfall data is purchased from the Department of Hydrology and Meteorology, Babarmahal, Kathmandu, Nepal. The data constitutes the location of the meteorological station network and corresponding daily rainfall records from 2014 to 2022.

3.2.1 Model Description

The Markov deterioration hazard model is the probabilistic model based on survival analysis and hazard function for multi-condition ratings.

This model helps to predict the hazard rate, life expectancies, and deterioration curves of roads given the historical inspection results and other variables concerning various environmental impacts such as traffic volume, weather, temperature, axle loads, etc. These variables are termed explanatory variables. For the application of the Markov hazard model, the following assumptions must hold true.

Assumptions of the Markov model are : (a) there have been no maintenance and repair activities imposed and no measurement errors during the inspection period and (b) the deterioration process of the road section occurs naturally as its condition state getting worsens over the year[14].

This deterioration process is explained graphically in Figure 3.1 with blue round marks. At time τ_0 the condition state is in a good state with $i = 1$. Over the year condition state, i $(i = 1, 2, \dots, J)$ deteriorates and falls into a worse condition. Inspection is carried out at τ_A and τ_B. The condition state at inspection points is known but there is difficulty to trace exactly when the condition states transitioned, τ_1 and τ_2 in Figure 3.1 , between the two inspection points. Thus, it is noted that condition state 2 at any arbitrary future time τ_1 cannot be deterministically predicted. Moreover, the condition state at each time point in the time axis is restricted to the time at which the inspection is done.

In Figure 3.1, τ represents the calendar time. The deterioration of the road pavement starts immediately after its opening to public use at an initial time τ_0. The condition state is expressed by ranks representing condition state variable i $(i = 1, 2, \dots, J)$, where $i = 1$ represents the good or new situation. The increments of condition state i indicates progressing deterioration and $i = J$ indicate its service limit (absorbing state of the Markov chain). In Figure 3.2 with green round marks, for each discrete time τ_i $(i = 1, 2, \dots, J)$, on the x-axis, we can observe the condition state changing from i to $i + 1$. Therefore, τ_i refers to the time at which the transition from condition state i to $i + 1$ occurs.

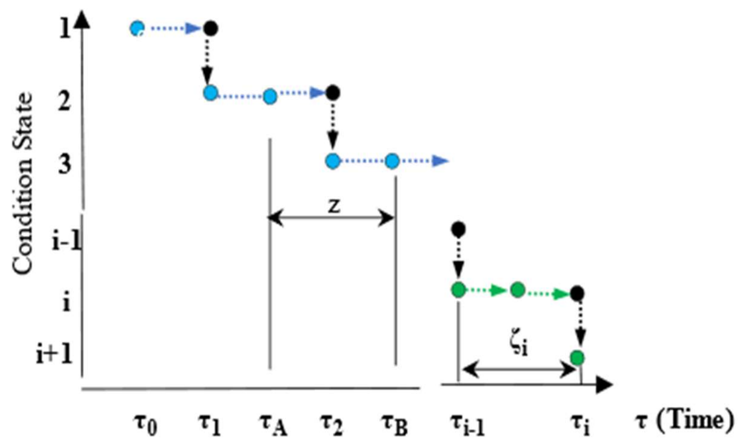

Figure 3.1 Deterioration process and inspection.

The data regarding the deterioration process can be obtained from the periodic inspection results. Since the continuous monitoring and inspection of infrastructure is difficult and cost-consuming, therefore normal practice is to conduct discrete periodic inspections during the service life of the infrastructure. The model assumes two periodic inspections at times τ_A and τ_B on the time axis such that its interval is denoted by Z ($Z = \tau_B$ - τ_A).

Figure 3.1 also explains the deterioration path of pavement condition using the concept of the Markov chain. When the deterioration condition state changes from i to $i+1$ (refer to green round marks) at τ_i, the duration it remained at condition state i can be expressed by ζ_i ($\zeta_i = \tau_i - \tau_{i-1}$). The life expectancy of a condition state i is assumed to be a stochastic variable with a probability density function $f_i(\zeta_i)$ and distribution function $F_i(\zeta_i)$. The distribution function $F_i(\zeta_i)$ represents the cumulative probability of the transition in the condition state for i to $i+1$, when i is set at the initial point $y_i = 0$ (time τ_{i-1}). The cumulative probability $F_i(y_i)$ of a transition in the condition state i during the time points interval $y_i = 0 \; to \; y_i \in [0, \infty]$ is defined as:

$$F_i(y_i) = \int_0^{y_i} f_i\ (\zeta_i) d\zeta_i \tag{3.1}$$

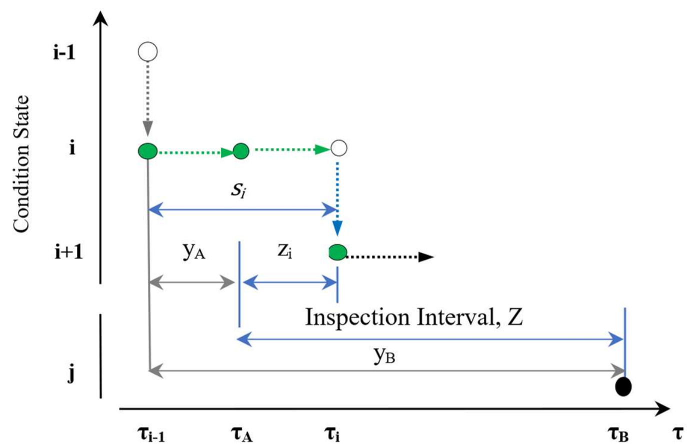

Figure 3.2 **Periodic inspection practice of the condition state states.**

Accordingly, the survival function $R_i(y_i)$ becomes $R_i(y_i) =$ Prob$\{\zeta_i \geq y_i\} = 1 - F_i(y_i)$. By using the exponential hazard function, it is possible to represent the deterioration process that satisfies the Markov condition. The probability density $\lambda_i(y_i)$, which is referred to as the hazard function, is defined in the domain $[0, \infty]$ as:

$$\lambda_i(y_i) = \frac{f_i(y_i)}{R_i(y_i)} = \frac{\frac{dR_i(y_i)}{dy_i}}{R_i(y_i)} = \frac{e}{dy_i}\,(-logR_i(y_i)) \tag{3.2}$$

Using the hazard function $\lambda_i(y_i) = \theta_i$, the probability $R_i(y_i)$ that the life expectancy of the condition state i remains longer than y_i and its probability density function $f_i(\zeta_i)$ are expressed by the following:

$$R_i(y_i) = \exp\left[-\int_0^{y_i} \lambda_i(u)du\right] = \exp\,(-\theta_i y_i) \tag{3.3}$$

$$f_i(\zeta_i) = \theta_i \exp\,(-\theta_i \zeta_i) \tag{3.4}$$

Referring to Figure 3.3, it is supposed that at time τ_A, the condition state observed by inspection is $i\;(i = 1, 2, \ldots, J-1)$. The deterioration process in future times is uncertain. Among the infinite set of possible

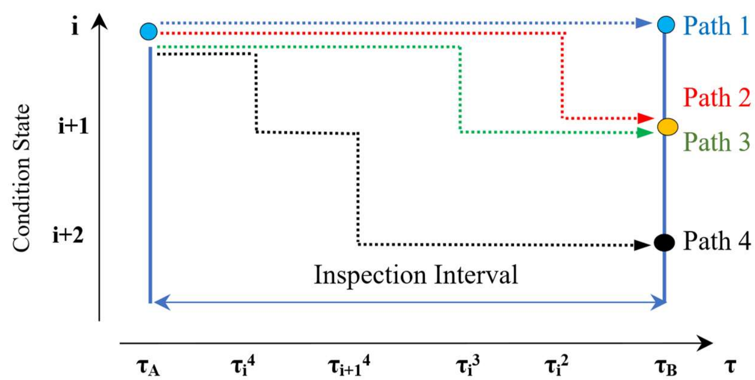

Figure 3.3 **Condition states and possible deterioration paths.**

scenarios describing the deterioration path, only one path is finally realized. For simplicity, there are four possible sample paths described as follows:

Path 1 indicates no transition in condition state i during the periodic inspection interval. Path 2 indicates the transition of the pavement from condition state i to $i+1$ at time τ_i^2. Path 3 indicates the transition of the pavement from condition state i to $i+1$at time τ_i^3. Path 4 indicates the transition of the pavement from condition state i to $i+1$ and $i+2$ at time τ_i^4 and τ_{i+1}^4 respectively. The condition state observed at τ_B is $i+2$. The transitions in the condition state are observed only at the time of periodic inspections (at τ_A and τ_B) and it is not possible to obtain information about the time in which those transitions occurred (τ_i^4, τ_{i+1}^4, τ_i^3 , τ_i^2 etc.)

3.2.1 Markov Transition Probability

The transition process of the condition state for road pavement is uncertain and forecasting future states cannot be done deterministically. The Markov transition probability is used to represent the uncertain transition of the condition state during two points in time. In other words, Markov transition probabilities are defined to forecast the deterioration of pavement using the periodic inspection process shown in Figure 3.2. The observed condition state of the component at time τ_A is expressed by using the condition state variable $h(\tau_A)$. If the condition state observed at time $\tau_A = i$, a Markov transition probability, given a condition state $h(\tau_A) = i$ observed at time τ_A, defines the probability that the condition state at a future time τ_B will change to $h(\tau_B) = j$, that is

$$\text{Prob}[h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \tag{3.5}$$

The Markov transition probabilities matrix can be defined by using the transition probabilities between each pair of condition states (i, j) as:

$$\prod = \left(\begin{bmatrix} \pi_{11} & \cdots & \pi_{1J} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{bmatrix}\right) \tag{3.6}$$

Where, $\pi_{ij} \geq 0$,

$\pi_{ij} = 0$ (when $i > j$) since the model does not consider the repair and $\sum_{j=1}^{J} \pi_{ij} = 1$.

The final state of deterioration is expressed by condition state J, which remains an absorbing state in the Markov chain if no repair is carried out. In this case $\pi_{JJ} = 1$.

3.2.3 Determination of Markov Transition Probabilities

From Figure 3.2 various deterioration paths are possible that are broadly classified into π_{ii} , π_{ii+1}, π_{ij} and π_{iJ}. The Markov transition probabilities for these possible paths are based on the exponential hazard model can be explained for the three cases considering the condition state observed at periodic inspection time point as shown in Figure 3.3.

Case 1: The condition state i does not change during the inspection interval Z: For a condition state i obtained at the inspection time point y_A, the probability that the same condition state is observed at a time point y_B $(= y_A + z)$ is expressed by:

$$\pi_{i\,i} = \text{Prob}[h(y_B) = i \mid h(y_A) = i]$$

$$\pi_{i\,i} = \exp(-\theta_i Z) \tag{3.7a}$$

The equation (3.7a) indicates that π_{ii} is dependent only on the hazard rate (θ_i) and inspection interval (Z). This shows it is also possible to estimate transition probability without using the deterministic value of the time points y_A and y_B.

Case 2 : The condition state changes from i to $i+1$ during the inspection interval Z : For a condition state i observed at inspection time point y_A to change to condition state $i+1$ at time point y_B, the transition is assumed to occur as 1) the condition state i remains constant between a time point y_A to a time point $s_i = y_A + z_i$, $(z_i \in [0, Z])$, 2) the condition state changes to $i+1$ at the time point $y_A + z_i$, and 3) it remains constant between $y_A + z_i$ and y_B. Although the exact time in which the condition state transition from i to $i+1$ cannot be traced by periodic inspection, it is assumed that the transition occurs at a time point $\bar{s_i} \in [y_A, y_B]$. The Markovian transition probability that the condition state change from i to $i+1$ during the time points y_A and y_B is expressed by:

$$\pi_{i\,i} = \text{Prob}[h(y_B) = i \mid h(y_A) = i]$$

$$\pi_{i\,i+1} = \frac{\theta_i}{\theta_i - \theta_{i+1}}\{-\exp(-\theta_i Z) + \exp(-\theta_{i+1} Z)\} \tag{3.7b}$$

where, $\pi_{i\,i+1} < 1$

Case 3 : The condition state changes from i to j ($j \geq i+2$) during the inspection interval Z : For a condition state i observed at the inspection time point y_A to change to condition state j at the time point y_B, the transition is assumed to occur as: 1) the condition state i remains constant between a time point y_A, $\bar{s}_i = y_A + \bar{z}_i \in [y_A, y_B]$, 2) the condition state changes to $i+1$ at the time point $\bar{s_i} = y_A + \bar{z}_i$, 3) the condition state $i+1$ remains constant during the time interval $\bar{s}_i = y_A + \bar{z}_i$, $\bar{s}_{i+1} = \bar{s}_i + \bar{z}_{i+1}$ $(\bar{s}_{i+1} \leq y_B)$, and at this time point changes to $i+2$. After repeating the same process 4) the condition state changes to j at some time point $\bar{s}_{j-1}$ $(\leq y_B)$ remains constant until the time point y_B.

The Markovian transition probability that the condition state change from i to j $(j \geq\ j+2)$ during the time points y_A and y_B is expressed by:

$$\pi_{i\,i} = \text{Prob}[h(y_B)\ =\ i \mid h(y_A)\ =\ i]$$

$$\pi_{ij} = \sum_{k=i}^{j} \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} \exp(-\theta_k Z) \tag{3.7c}$$

Where,

$\prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} = 1, at\ (k \leq i+1)$ and

$\prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} = 1\ at\ (k \geq j)$.

In equation (3.7c) , π_{ij} $[0 < \pi_{ij} < 1]$, and π_{iJ} is arranged using the Markov transition probabilities conditions as follows:

$$\pi_{iJ} = 1 - \sum_{j=1}^{j-1} \pi_{ij} \tag{3.7d}$$

In equation (3.7a) ~ (3.7d) the multistage exponential hazard model has been defined. However, considering the explanatory variable to estimate hazard rate θ_i which is defined as the function of explanatory variables $\mathbf{x^k}$ and unknown parameters $\boldsymbol{\beta}_\mathbf{i}$. where $\beta_i = (\beta_{i,1}, \ldots, \beta_{i,m})$ and $\boldsymbol{m} = (1, 2, \ldots, M)$ is the number of explanatory variable and $k = (\ 1, 2, \ldots, K)$ is an individual sample of inspection data.

$$\theta_i^k\ =\ f(\boldsymbol{x^k} \colon \boldsymbol{\beta_i}) \tag{3.8}$$

In summary, the elements of MTP matrix π_{iJ} are estimated using $\pi_{iJ}\ (Z^k, \boldsymbol{x^k} \colon \boldsymbol{\beta_i})$. The unknown parameter $\boldsymbol{\beta_i}$ $(i = 1, 2, \ldots\ , \ J-1)$ is determined with Bayesian estimation method to obtain the hazard function $\theta_i^k (i = 1, 2, \ldots, J-1)$, the life expectancy of each condition state i can be defined by means of the survival function $R_i(y_i^k)$.

$$LE_i^k\ =\ \int_0^\infty exp\ (-\exp\ (\theta_i^k y_i^k) dy_i^k\ \ =\ \frac{1}{\theta_i^k} \tag{3.9}$$

Life expectancy from i to J can be estimated using

$$LE_i^J = \sum_{i=1}^{J-1} LE_i^k. \tag{3.10}$$

The MTP matrix $\prod$ defined in equation (3.6) can be composed by aggregating π_{ij} from equation (3.7a) – (3.7d). For detailed description it is recommended to refer the reference Tsuda et al., 2006[13].

3.2.4 Determination of Markov Transition Probabilities

Bayesian estimation is an iterative method of statistical inference that involves using prior knowledge and data to estimate the parameters of a model. In the context of a Markov hazard model, Bayesian estimation can be particularly useful to estimate the unknown parameter $\boldsymbol{\beta_i}$ for several reasons. They are (a) Incorporation of prior knowledge: In Bayesian estimation, it allows us to use prior knowledge about the parameters of the model to inform our estimates. This can be particularly useful in case of some prior knowledge about the parameters that we are trying to estimate. (b) Robustness to small sample sizes: Bayesian estimation can be more robust to small sample sizes compared to classical methods, as it allows us to incorporate prior knowledge and make use of partial information. (c) Quantification of uncertainty: Bayesian estimation allows to quantify the uncertainty associated with estimates, which can be useful for decision making and risk assessment. And (d) Flexibility: Bayesian estimation is generally more flexible compared to classical methods, as it allows to specify different prior distributions and consider different model structures.

In Bayesian statistics, the posterior distribution of parameter is estimated by using a likelihood function, inspection data and an assumed prior distribution of the model parameters. Hence, the posterior distribution $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ is proportional to the likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ and prior distribution $\pi(\boldsymbol{\beta})$[15]. That is:

$$\pi(\boldsymbol{\beta}|\boldsymbol{\xi}) \propto \ L(\boldsymbol{\beta}|\boldsymbol{\xi})\,\pi(\boldsymbol{\beta}) \tag{3.11}$$

where, $\boldsymbol{\beta}$ is a probabilistic random variable with prior probability density function $\pi(\boldsymbol{\beta})$ and $\boldsymbol{\xi}$ is the observed inspection data. The posterior probability density function of unknown parameter $\boldsymbol{\beta}$ can be defined by the simplest form of Bayes Theorem as:

$$\pi(\boldsymbol{\beta}|\boldsymbol{\xi}) = \frac{L\,(\boldsymbol{\beta}|\boldsymbol{\xi})\ \pi(\boldsymbol{\beta})}{\int L\,(\boldsymbol{\beta}|\boldsymbol{\xi})\pi(\boldsymbol{\beta})\,d\beta} \tag{3.12}$$

Where, $L(\boldsymbol{\xi}) = \int L(\boldsymbol{\beta}|\boldsymbol{\xi})\pi(\boldsymbol{\beta})d\beta$ is the marginal probability of $\boldsymbol{\xi}$, called the normalizing constant.

In conclusion, Bayesian estimation can be a useful method for estimating the parameters of a Markov hazard model, particularly with limited data or prior knowledge that need to incorporate into estimates.

The Bayesian method for estimation can be summarized in 3 steps:

Step 1: Define the prior probability distribution $\pi(\boldsymbol{\beta})$. **Step 2**: Define the likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ by using newly obtained data $\bar{\boldsymbol{\xi}}$. **Step 3**: Modify the prior distribution $\pi(\boldsymbol{\beta})$ using the Bayes' rule and update the posterior distribution $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ for parameter $\boldsymbol{\beta}$.

In this paper, we suppose that the observed data is defined by $\bar{\boldsymbol{\xi}} = (\bar{\xi}^1, \ldots, \bar{\xi}^k)$ and the inspection information of the inspection sample k is $\bar{\boldsymbol{\xi}}^{\boldsymbol{k}} = (\bar{\delta}_{ij}^k, \bar{\mathbf{z}}^{\boldsymbol{k}}, \bar{\boldsymbol{x}}^{\boldsymbol{k}})$. (The likelihood function $L(\boldsymbol{\beta}|\boldsymbol{\xi})$ based on Bayes Rule is defined by using $\pi_{ij}(z)$ such that:

$$L(\boldsymbol{\beta}|\boldsymbol{\xi}) = \prod_{i=1}^{j-1}\prod_{j=i}^{J}\prod_{k=1}^{K}\{\sum_{h=i}^{j}\prod_{l=i}^{h-1}\frac{\theta_l^k}{\theta_l^k - \theta_h^k}\cdot\cdot\prod_{l=h}^{j-1}\frac{\theta_l^k}{\theta_{l+1}^k - \theta_h^k}\exp\left(-\theta_h^k\bar{z}^k\right)\}^{\bar{\delta}_{ij}^k} \tag{3.13}$$

where, $\bar{\delta}_{ij}^k$ is a dummy variable, whose value is 1 when $h(\tau_A^k) = i$) and $h(\tau_B^k) = j$, otherwise 0.

Referring to step 1, to define the prior probability density distribution function of unknown parameter $\boldsymbol{\beta}$, we defined a conjugate prior probability density function and assume that the prior probability density distribution function of unknown parameter $\boldsymbol{\beta}$ follows the conjugate multidimensional normal distribution such that $\boldsymbol{\beta_i} \sim \boldsymbol{N_M}$ $(\mu_i, \sum_i)$. This assumption is essential to overcome the computational problems related to the non-convergence of estimation results and to derive a similar function for the posterior probability density function. Thus, we can express the probability density function of the M-dimensional normal distribution $\boldsymbol{N_M}$ $(\mu_i, \sum_i)$ as:

$$g(\boldsymbol{\beta}_i|\mu_i, \boldsymbol{\Sigma_i}) = \frac{1}{(2\pi)^{\frac{M}{2}}\sqrt{|\Sigma_i|}} \cdot \exp\left\{-\frac{1}{2}(\boldsymbol{\beta}_i - \mu_i)\,\boldsymbol{\Sigma}_i^{-1}(\boldsymbol{\beta_i} - \mu_i)'\right\} \tag{3.14}$$

where, μ_i represents the prior expectation vector (or mean) of $\boldsymbol{N_M}$ $(\mu_i, \sum_i)$ and $\boldsymbol{\Sigma_i}$ is the prior variance – covariance matrix. The symbol $'$ denotes the transposition. Substituting the value from equation (3.13) and equation (3.14), the posterior density function $\pi(\boldsymbol{\beta}|\boldsymbol{\xi})$ in equation (11) can be defined as:

$$\pi(\boldsymbol{\beta}|\bar{\boldsymbol{\xi}}) \propto L(\boldsymbol{\beta}|\bar{\boldsymbol{\xi}}) \cdot \prod_{i=1}^{j-1} g(\boldsymbol{\beta_i}|\mu_i, \boldsymbol{\Sigma_i})$$

$$\pi(\boldsymbol{\beta}|\bar{\boldsymbol{\xi}}) \propto \prod_{i=1}^{j-1}\prod_{j=i}^{J}\prod_{k=1}^{K}\{\sum_{h=i}^{j}\prod_{l=i}^{h-1}\frac{\theta_l^k}{\theta_l^k - \theta_h^k} \cdot \prod_{l=h}^{j-1}\frac{\theta_l^k}{\theta_{l+1}^k - \theta_h^k}\exp(-\theta_h^k \bar{z}^k)\}^{\bar{\delta}_{ij}^k} \cdot \frac{1}{(2\pi)^{\frac{M}{2}}\sqrt{|\Sigma_i|}}\exp\left\{-\frac{1}{2}(\beta_i - \mu_i)\,\Sigma_i^{-1}(\beta_i - \mu_i)'\right\} \tag{3.15}$$

However, the normalizing constant $L(\boldsymbol{\xi}) = \int L(\boldsymbol{\beta}|\boldsymbol{\xi}) \prod_{i=1}^{j-1} g(\boldsymbol{\beta_i}|\mu_i, \boldsymbol{\Sigma_i}) d\boldsymbol{\beta}$ is difficult to calculate. To overcome such limitation, we use Metropolis – Hasting algorithm often known as M-H algorithm in Markov chain Monte Carlo (MCMC) simulation to directly obtain the statistical value regarding the posterior distribution of parameters [14]. This method is suitable and can be applied when the normalizing constant for density function is not known or difficult to calculate[16]. The M-H algorithm operates as follows:

Step 1: Define the initial value of the parameter vector $\beta(0)$. **Step 2**: Calculate current probability density $\pi(\beta(n))$ by using current $\beta(n)$. **Step 3**:

Find a candidate value as $\tilde{\beta}(n) = \beta(n) + \varepsilon(n) \sim N\ (0, \sigma^2)$ where ε is the step width of the random walks. **Step 4**: Calculate the proposal density by using $\tilde{\beta}(n)$ as a candidate parameter $\pi\left(\tilde{\beta}(n)\right)$. **Step 5**: Apply the updating rule by comparing $\pi(\tilde{\beta}(n))$ and $\pi\big(\beta(n)\big)$ with the following conditions.

$$\beta(n+1) = \begin{cases} \pi\left(\tilde{\beta}(n)\right) > \pi\big(\beta(n)\big), \beta(n+1) = \tilde{\beta}(n) \\ \pi\left(\tilde{\beta}(n)\right) \leq \pi\big(\beta(n)\big), \begin{cases} R \leq r, \beta(n+1) = \tilde{\beta}(n) \\ Else, \beta(n+1) = \beta(n) \end{cases} \end{cases} \quad (3.16)$$

Where, $r = \pi\left(\tilde{\beta}(n)\right)/\pi\big(\beta(n)\big)$, and R is a standard uniform for $R \sim U\ (0,1)$.

Then sufficiently large numbers of iterations from step 2 to step 5 are done, until sequence β^n becomes a stationary condition (that is close to convergence). Burn-in samples are cut and the average of sample parameters are taken.

The M-H algorithm also generates Markov chains as the transition probabilities from $\beta(n)$ to $\beta(n+1)$ that independent of $\beta(0)$. The MCMC does not include any method to confirm that the initial value $\beta(0)$ reaches stationary distribution. To check the Markov chain reaches the convergence to a maximum, Geweke's test is used. Geweke's test takes two sample groups (n_1, n_2) from the first 10% and the last 50% of the Markov chain. If the mean of the two groups is equal, it indicates the chain is stationary. A modified z-test can be used to compare the two samples and the resulting statistics are termed as Geweke's z-score. The detailed description of M-H algorithm and Geweke's test to confirm the convergence of the Markov chain can be referred to Han et. al., (2014)[17].

3.3 Empirical Analysis

Among the four measures identified for a performance measure, DOR considers the following two primary measures: i) surface roughness and ii) surface distress of pavement to determine how well the pavement is performing and meets the serviceability requirement of the road. The

Bayesian estimation for the Markov hazard model is carried out with the actual inspection data based on these two performance measures of road pavement of SRNs. The inspection data set includes the result of two inspection intervals: Z, and characteristic variable: x. To apply Markov transition probability the condition rating shown in Table 3.1 and Table 3.2 are used to rate the pavement based on SDI and IRI respectively. In this study, average annual daily traffic and cumulative monsoon rainfall are considered as traffic and environmental characteristic variables respectively. There are primarily two types of pavement (a) Surface treatment over granular base and (b) Asphalt Material over granular base. These two categories of pavement are represented by 0 and 1 respectively as categorical explanatory variables. For analysis, all quantitative value of the characteristic variable is normalized so that the maximum value becomes 1. The total number of 4,967 sets of road section data based on SDI and 4,317 sets of road section data based on IRI satisfying the Markov condition were analyzed. These data sets are used in this paper to estimate the parameters of the exponential hazard function.

3.3.1 Surface Roughness

Surface Roughness is closely related to the pavement condition and the vehicle operating cost increases with an increase in the roughness of the IRI expressed in m/km is used to provide a common scale for recording road roughness. A vehicle-mounted Bump Integrator is a response-type instrument to measure the surface roughness annually[10]. The road condition and the condition state based on IRI are shown in Table 3.1

Table 3.1 Road Roughness based on IRI

IRI Value	Condition	Condition State
<4	Good	1
4-6	Fair	2

6-8	Poor	3
>8	Bad	4

3.3.2 Surface Distress

Surface Distress provides a visual indication of pavement deterioration. The common approach is to quantity pavement distress by means of visual inspection by highway experts. The pavement distress characteristics for paved and unpaved roads vary widely. The road condition and the condition state based on SDI adopted in Nepal is shown in **Table 3.2**.

Table 3.2 Road Roughness based on SDI

SDI Value	Condition	Condition State
< 1.7	Good	1
1.8 – 3.0	Fair	2
3.1 – 5.0	Poor	3

3.3.3 Rainfall

Rainfall is an important environmental factor having damaging effects on road pavement. In Nepal, the monsoon is the major source of rainfall. There are more than 1,000 meteorological stations over Nepal for rainfall observation under the Department of Hydrology and Meteorology. The meteorological stations having a complete set of rainfall records throughout the year are only considered for the study. For example, in the year 2022, rainfall data from 407 out of 1012 meteorological stations are considered for study.

The daily rainfall measurement data by the meteorological station network is summed to determine the cumulative annual monsoon rainfall (C_m) at each station. Inverse distance weighting (IDW), a GIS application to interpolate between stations of known rainfall value, is used to generate cumulative rainfall distribution (mm) over Nepal.

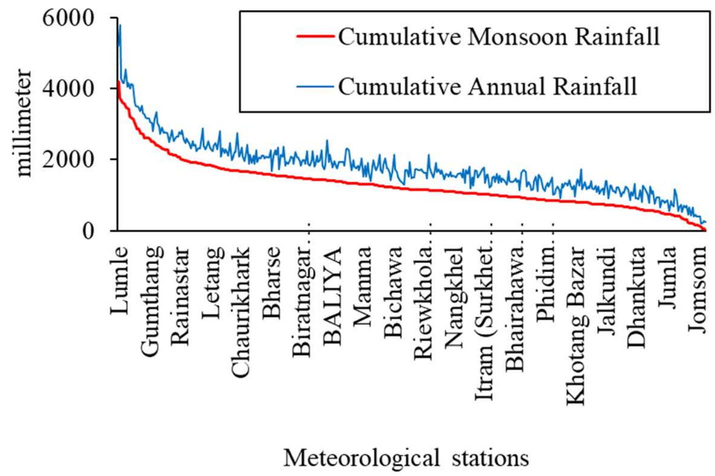

Figure 3.5 Rainfall in mm, 2022

Figure 3.4 shows the location of meteorological stations, SRN and Cumulative Monsoon Rainfall Distribution in millimetres for year 2022. Approximately 80 percent of the annual rainfall takes place from June till

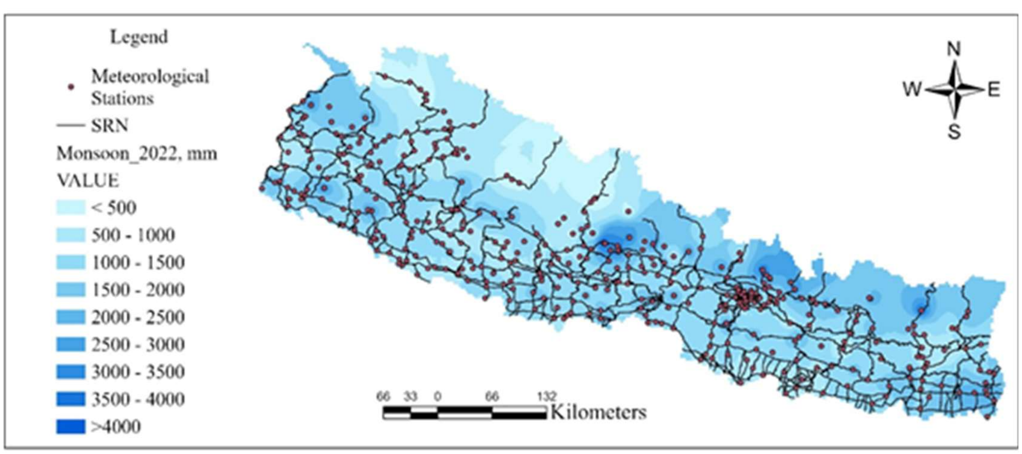

Figure 3.4 SRN and CMR Distribution, mm, 2022

September[18–20]. A plot of the cumulative annual rainfall and cumulative monsoon rainfall measurements from 407 meteorological stations in 2022 is shown in Figure 3.5.

3.4 Results

3.4.1 Average Markov transition probability

The Markov transition probabilities matrix for each sample is estimated by using the exponential hazard model and the average MTP matrix is determined which are presented in Table 3.3 and Table 3.4.

Table 3.3 MTP Matrix from estimation results - SDI

Rating	1	2	3
1	0.556	0.404	0.040
2	-	0.845	0.155
3	-	-	1

Table 3.4 MTP Matrix from estimation results - IRI

Rating	1	2	3	4
1	0.631	0.309	0.054	0.006
2	-	0.712	0.248	0.040
3	-	-	0.757	0.243
4	-	-	-	1

Table 3.5 Exponential Hazard Model Results - SDI

Rating	Const.; $\boldsymbol{\beta_0}$	AADT; $\boldsymbol{\beta_{i1}}$	C_m; $\boldsymbol{\beta_{i2}}$	P. Type; $\boldsymbol{\beta_{i3}}$
1	0.017 (0.511)	-3.257 (1.075)	-1.131 (-0.558)	-0.559 (-0.722)

2	-1.810 (0.909)	-4.645 (-0.282)	1.123 (-0.657)	-0.507 (0.171)

Table 3.6 Exponential Hazard Model Results - SDI

Rating	Const.; β_0	AADT; β_{i1}	C_m; β_{i2}	P. Type; β_{i3}
1	-0.232 (-1.360)	-2.393 (0.796)	-1.208 (0.883)	-0.466 (0.486)
2	-0.618 (0.438)	-0.625 (1.503)	-1.257 (-1.056)	-0.671 (-1.096)
3	-1.258 (-1.347)	-1.620 (1.930)	0.345 (0.629)	-0.130 (-0.197)

For SDI, there are 3 rating and 3 explanatory variables, this gives a total of 8 unknown parameters $\boldsymbol{\beta}$. Similarly, for IRI, there are 4 rating and 3 explanatory variables, this gives a total of 12 unknown parameters $\boldsymbol{\beta}$. The Bayesian estimated results of the unknown parameter $\boldsymbol{\beta}$ for SDI and IRI are shown in Table 3.5 and Table 3.6 with the respective Geweke's test value of each explanatory variable.

3.4.2 Hazard Rate and Life Expectancy

The hazard rate for each transition is estimated using equation (8). Since the two major types of pavement STGB and AMGB differ in pavement thickness, strength, construction technology and cost etc. the hazard rate are estimated separately. The life expectancies for each transition are estimated using equation (9) and they are graphically presented in Figure 3.6 and Figure 3.7. The life expectancies for two major types of pavement STGB and AMGB are also presented separately.

To understand the change in condition state over time visually, it is convenient to express the deterioration process by curves. The expected

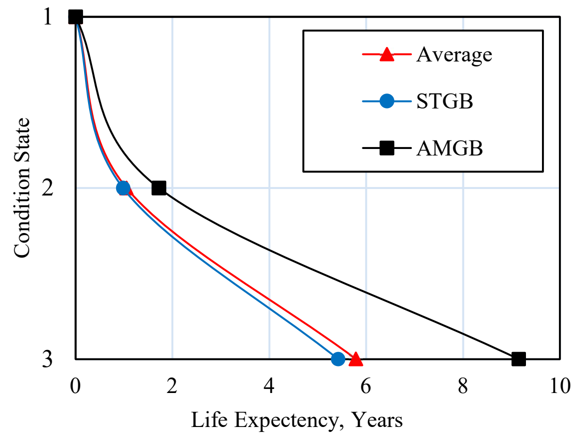

Figure 3.6 Expected deterioration path for pavement – SDI

deterioration path can be represented by a curve describing the average deterioration process during the life expectancy rating as shown in Figure 3.6 and Figure 3.7. The results of the study for the effect of monsoons on pavement deterioration is also presented. The expected deterioration path for the 90th percentile and 10th percentile cumulative monsoon for two major types of pavement STGB and AMGB is shown in Figure 3.8 and Figure 3.9 respectively.

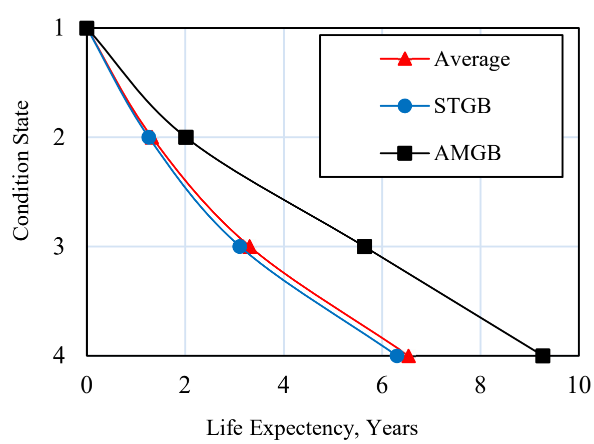

Figure 3.7 Expected deterioration path for pavement - IRI

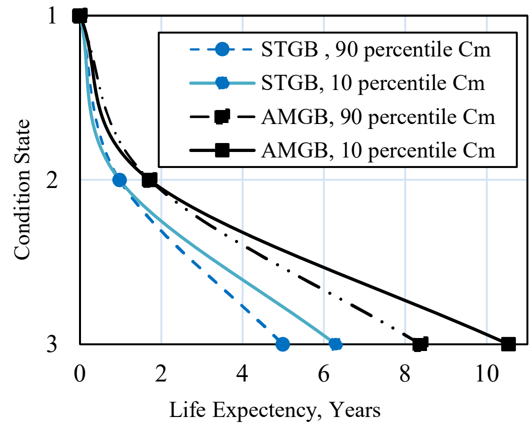

Figure 3.8 Expected deterioration path of pavement for C_m – SDI

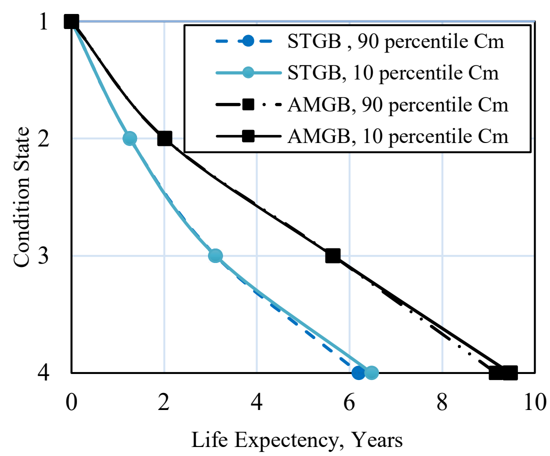

Figure 3.9 Expected deterioration path of pavement for C_m - IRI

Further, it is also important to understand the time series variation of the condition state distribution of the entire infrastructure system or in our case the entire strategic road network for effective planning of asset management. The time-series variation of the condition state distribution is analyzed using the MTP.

Let us consider a case where the entire road network is new at initial time t ($t = 0$). The condition state ranking of all equals to 1 (SDI < 1.7) and we define the initial value of the state vector as $X_t = (1, 0, 0)$. Then using

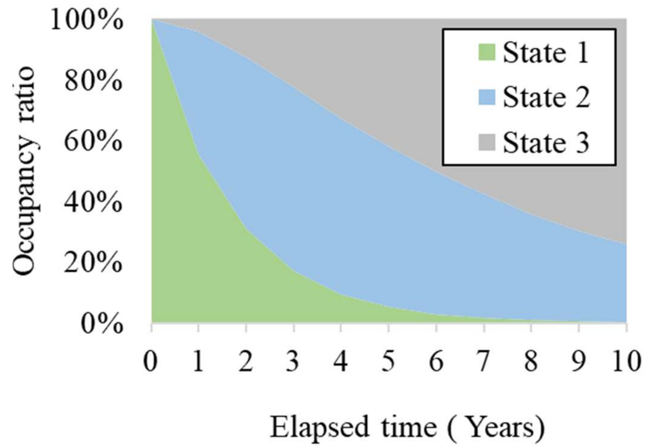

Figure 3.10 Condition state of network by elapsed years – SDI

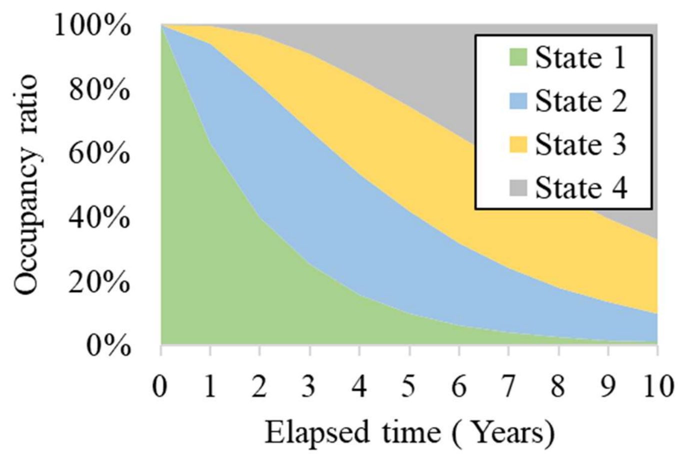

Figure 3.11 Condition state of network by elapsed years - IRI

the MTP the time-series variation of the condition state is calculated for consecutive 10 times. Since the inspection interval is 1 year, repeating the calculation 10 times will represent the condition state distribution over a period of 10 years.

Figure 3.10 shows the transition of the condition state distribution when MTP in Table 3.4 is estimated using the SDI for condition state ranking and similarly, Figure 3.11 shows the transition of the condition state distribution when MTP in Table 3.5 is estimated using the IRI for condition state ranking. From the Figure 3.10 and Figure 3.11 we can observe that the deterioration process and increasing occupancy rates of higher condition states with elapse of time.

Referring to Figure 3.10 and Figure 3.11, after 5 years, there are approximately 5.3% and 10% of the entire road network in good condition considering SDI and IRI respectively. In addition, approximately 74% and 67% of the entire road network will be in poor condition considering SDI and IRI respectively demanding huge capital reinvestment to reinstate into good condition.

3.5 Discussion

The road pavement mainly deteriorates under the action of traffic and environmental factors. But, the study shows contradicting results that the traffic parameter (in this study average annual daily traffic) has negative deteriorating action on the pavement. This may be due to the unit adopted for the measurement of traffic volume in Nepal. The traffic volume is measured in PCU by converting different types of vehicles counts multiplied by their equivalence factor regardless of the loading condition. But different commercial vehicles have different laden weights and axle configurations. Their conversion to equivalent standard axle load and the number of repetitions during the service life are important factors in the structural design of flexible pavements. Therefore, the traffic parameter if quantified in terms of ESAL (Equivalent Single Axle Load) may give a better estimate of the pavement deterioration process.

The environmental parameter i.e. cumulative monsoon rainfall (C_m) measured in millimeters, shows deterioration action on the pavement in the later condition states. The deterioration process of the pavement is estimated excluding the traffic parameter (AADT) and including the environmental parameter (C_m) only in the fair to poor condition state for SDI and in the poor to bad condition state for IRI.

The deterioration curve corresponding to SDI and IRI shows the life expectancy of the road networks. In the context of Nepal, only SDI is considered as the prime indicator for the choice of road section for periodic maintenance works. Periodic maintenance complemented by routine and recurrent maintenance work is performed to improve and extend the service life of the pavement. There are two major types of pavements in Nepal: STGB (surface treatment over granular base) – type and AMGB (asphalt material over granular base)- type. The current practice suggests an interval of 5-8 years for periodic maintenance irrespective of pavement type[11]. The deterioration curves indicate that the rate of deterioration is high, and this interval is leading to further degradation of the road condition beyond the scope of periodic maintenance. This is more significant for STGB type roads which will demand expensive maintenance alternatives such as rehabilitation and reconstruction in future to reinstate into good condition.

The life expectancies of STGB and life expectancies of AMGB type roads are shown graphically in Figure 3.6 to Figure 3.9. The average deterioration period in years during the life expectancy of the rating i.e., from the time the rating is reached to the next rating is attained is known. This information can provide an actual time frame to plan efficient inspection intervals and maintenance planning.

3.6 Conclusion

In addition to the construction of new road infrastructure, it is also necessary to implement the concepts of road asset management for effective and efficient utilization of road assets during their service life in the future. In this study, Markov deterioration hazard model is applied for deterioration forecasting of SRN in Nepal. The study indicates the deterioration rate is high. The total life expectancy of roads considering SDI and IRI is 5.79 years and 6.54 years respectively. The deterioration curves presented in Figure 3.6 to Figure 3.9 can be used to forecast the future condition state of the road network and predict the remaining life expectancies. IRI, which is an internationally accepted performance parameter for maintenance decisions and prioritizing processes but not considered in Nepal, can as well used at network level for screening of the road sections for periodic maintenance. Further, it is possible to choose IRI as performance measure over SDI for pavement decision-making and prioritization processes.

However, there are still many aspects for future study. First, the study is limited to only average annual daily traffic as the explanatory variable for traffic. The other variable like commercial vehicles is an observable characteristic variable, it cannot be included in this study due to insufficient data sets. The commercial traffic volume expressed in ESAL can help better predict the deterioration process. Second, environmental factors like temperature can also be included as explanatory variables in future studies. Third, the study presents the average deterioration process of the entire road network, but the road network itself is composed of heterogenous road infrastructures that can be grouped into different infrastructure groups considering categorical variables. By using the mixed Markov deterioration hazard model, the deterioration characteristics of individual groups of road infrastructure can be studied. It is expected to include the above-mentioned explanatory variables in the future with sufficient inspection data to expand the study for improved forecasting of the deterioration process of road infrastructure.

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Chapter 4 : Modeling Pavement Deterioration on Nepal's National Highways: Integrating Rainfall Factor in a Hazard Analysis

4.1 Introduction

Pavement deterioration is a significant challenge in road asset management, especially in developing countries like Nepal, where varying climatic conditions, mixed and high traffic volumes challenge maintenance strategies. Effective road asset management aims to minimize the life cycle costs of road infrastructure by ensuring timely inspections, accurate predictions of degradation, and the implementation of periodic maintenance measures. However, predicting pavement deterioration in regions with complex environmental variables, such as monsoons and diverse topography, require advanced analytical approaches.

In Nepal the road network of national highways, feeder roads and sub-urban roads is collectively termed as the Strategic Road Network (SRN). Maintaining these roads is particularly challenging due to Nepal's topography and diverse climate, which ranges from alpine in the Himalayas to temperate and subtropical monsoon climates in the mid-hills and plains [21]. In Nepal, the majority of rainfall events occur during the monsoon season, accounting for about 80% of the yearly rainfall from June to September[18,19]. This intense and prolonged precipitation significantly affects road conditions, expediting pavement deterioration and imposing challenges to traffic safety and maintenance planning. The Department of Roads (DOR) conducts annual road maintenance planning to maintain the SRN in serviceable condition. However, as this method does not enable pavement condition prediction, it is challenging to implement long-term maintenance planning, which is essential for effective asset management and strategic decision-making concerning budget allocation and road network performance. To address these challenges, predictive models that consider both traffic and environmental factors are essential. However, such pavement deterioration models specifically developed for Nepal's unique traffic and climatic conditions are not available in practice.

In light of these limitations, relying on various pavement prediction models becomes essential for effective long-term planning. Referring to pavement management guidelines, commonly utilized models for predicting pavement conditions include deterministic, probabilistic, Bayesian, and expert-based methods [22]. This study adopts Markov deterioration hazard models, a probabilistic approach, to study pavement deterioration while considering the impact of traffic and environmental factors. The term 'hazard' in the pavement deterioration model refers to the instantaneous probability rate of deterioration over time.

The monsoon is considered as the environmental explanatory variable. The value assigned for the road section under study is the interpolated value based on the rainfall measurement from the meteorological stations. This study also compares the effectiveness of two interpolation techniques (a) Inverse Distance Weighted (IDW) and (b) Empirical Bayesian Kriging 3D (EBK3D) for estimating monsoon parameters. These methods enable the distribution of Cumulative Monsoon Rainfall (CMR) data to be integrated into the Markov model as an explanatory variable, enhancing the predictive accuracy of pavement deterioration forecasts.

From an academic perspective, predicting pavement deterioration in developing country like Nepal presents significant challenges due to limited data availability and considerable variability in environmental and traffic factors. Although Tsuda et al. (2006)[13] have provided a robust foundation with the Markov deterioration hazard model, its application to road pavements in South Asia, where climatic conditions such as monsoons having significant influence, remain underexplored. This study attempts to address these gaps by applying a Markov deterioration hazard model to Nepal's road network and climatic conditions. This study seeks to provide valuable insights that can enhance pavement deterioration prediction not only in Nepal but also in other regions with similar climatic and infrastructure challenges.

4.2 Literature Review

DOR established in 1962 is a government institution responsible for the development and upkeep of the SRN through its various construction projects and maintenance divisions [3]. The necessary fund for repair and maintenance of the SRN are provided by the Roads Board Nepal (RBN) to various road division offices. Using the RBN fund, the DOR conducts road pavements condition surveys every year. Pavement performance indicators such as the Surface Distress Index (SDI) and International Roughness Index (IRI) are recorded. Similarly traffic data in the road network are measured as Annual Average Daily Traffic (AADT). Using these data, the process for planning and prioritizing the various maintenance strategies is prepared by DOR in the form of an integrated annual road maintenance plan to be executed in the following fiscal year for all road maintenance division offices under DOR [11]. The approach for planned maintenance and the detailed guidelines for road screening and ranking are outlined in the "Standard Procedure for Periodic Maintenance Planning", published by the DOR Maintenance Branch in November 2005. This policy document considers the SDI as the key pavement performance parameter [11]. Although the present annual road maintenance plan supports the maintenance plan for a year, it is essential to have a comprehensive road asset management system to support long-term maintenance planning.

The Highway Development and Management (HDM-4) model is a widely recognized deterministic tool used for predicting pavement deterioration. Neighboring countries like Bangladesh and India also use HDM-4 for pavement maintenance planning. The Department of Roads and Highway in Bangladesh uses HDM-4 as part of its Road Maintenance and Management System [23]. Similarly in India, HDM-4 is used for road deterioration prediction over time and under varying traffic and environmental conditions [24]. Moreover, HDM-4 is a deterministic model, and it is necessary to calibrate HDM-4 deterioration models to adapt to specific traffic characteristics, terrain, soil types, climatic conditions, and pavement composition of the region where they are applied. Additionally implementing HDM-4 poses challenges in many developing countries, where budget constraints, calibration in application, verification and adaptation level for long term make it difficult to meet the method's high data requirements [24,25].

However, probabilistic models are suitable for scenarios where variability and uncertainty are high such as pavement deterioration prediction. Tsuda et al. (2006) introduced a Markov deterioration hazard model for predicting pavement deterioration that has been widely referenced for its ability to model deterioration processes [13]. Kobayashi et al. (2010) expanded on this by integrating Bayesian estimation methods to improve the robustness of deterioration forecasts [15,17]. These studies provide a strong foundation for applying Markov models to pavement management systems, making it an essential tool in the context of pavement management systems.

Environmental factors, particularly rainfall, significantly contribute to accelerated pavement deterioration. The distress in bituminous pavement is induced by moisture damage in the forms of raveling, potholes etc. resulting from intense rainfall [26]. In Nepal, monsoon rainfall is predominant [18–20], leading to increased moisture infiltration into the underlying pavement layer, weakened subgrade support, and subsequent surface distress. The rainwater penetrates pavement cracks and weakens the underlying layers. Pavement damages caused by rain water accompanied by poor drainage is particularly pronounced in wet climates and areas subjected to freezing [27]. The increase in moisture in the

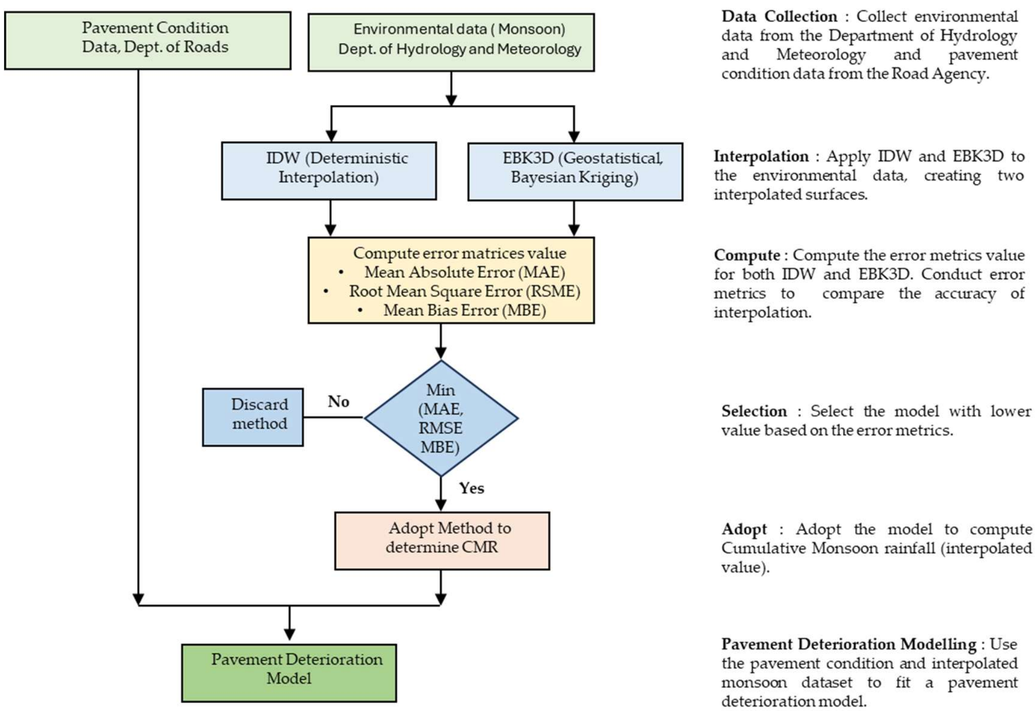

Figure 4.1 Pavement Deterioration Modeling Framework.

underlying layer increase both the fatigue strain and the permanent deformation strain of the pavement [28]. Excessive rainfall can lead to increased roughness which results in faster deterioration rates and reduced service life [29]. The Department of Hydrology and Meteorology (DHM) in Nepal operates a network of hydrological and meteorological stations that records essential environmental data which can be analyzed to study its impact on infrastructure [30]. However, the uneven location of meteorological stations and the fact that rainfall data from the meteorological stations are not specifically collected for road infrastructure, make it challenging to directly assign to specific road section. To overcome this limitation, spatial interpolation techniques are essential to accurately estimate unknown rainfall values for corresponding road sections and assign them as an explanatory variable in pavement deterioration predictive models.

To estimate the monsoon rainfall distribution across Nepal, this study applies two interpolation methods IDW and EBK3D which are widely used in hydrological and environmental studies [31–33]. IDW is a simple and widely used deterministic method that assigns weights to known data points such that closer data points have a greater influence on the estimated value. However, it does not consider spatial correlations, limiting its effectiveness in complex terrains [34]. Conversely, EBK3D extends traditional kriging[35] into three dimensions, incorporating a Bayesian framework that accounts for uncertainty in variogram estimation and improves the interpolation accuracy for complex data distributions [33,36].

4.3 Methodology

This study employs a Markov deterioration hazard model to predict pavement deterioration, integrating environmental data, particularly CMR on road surface. The more accurate values obtained from two distinct interpolation techniques (a) IDW and (b) EBK3D to model environmental data are used to model the environmental data in this study. Figure-1 illustrates the framework for pavement deterioration modeling using the Markov deterioration hazard model. The methodology is structured into four main stages: data collection, data preprocessing, interpolation of rainfall data, and application of the Markov deterioration hazard model with Bayesian parameter estimation.

4.3.1 Data Collection

The data utilized in this study were collected from periodic inspection reports recorded in the road register of the Highway Management Information System (HMIS) at the DOR. This dataset includes information on pavement conditions and traffic volumes. Additionally, daily rainfall data was sourced from meteorological stations managed by the DHM.

4.3.1.1 Surface Distress Index (SDI)

DOR considers surface distress of pavement as an important indicator for assessing pavement performance and ensuring it meets the road's serviceability requirements. SDI quantifies pavement distress, including cracks, disintegration (potholes), deformations, texture deficiency, pavement edge defects and other forms of deterioration. In the context of Nepal civil engineers specializing in highways and pavement specialists perform inspection and measurements to assess and quantify pavement distress for each 1-kilometer road section. These data are then used to compute the SDI value for the surveyed road section. The method for determining the SDI value and interpretation of the results can differ based on the surveyor's judgement and expertise and the guidelines established by the respective road agencies.

DOR in Nepal adopts a six-level rating index, ranging from 0 to 5 for quantifying the surface distress using SDI. A rating of 0 represents a pavement surface without any defect whereas a rating of 5 represents the maximum possible defects. This rating scale was recommended by the World Bank and has been modified to address the requirement of DOR. The methodology for measurement of SDI is outlined in "Road Pavement Management, MRCU" [10].

4.3.1.2 Traffic Data

The traffic data are acquired from HMIS unit of DOR. The classified traffic count survey includes the counting and analysis of motorized and non-motorized vehicles at 160 traffic count stations located at the major junctions on the SRN of Nepal. The traffic data are represented as AADT expressed in Passenger Car Unit (PCUs) and utilized as an explanatory variable in the hazard model.

4.3.1.3 Rainfall Data

Rainfall data are acquired from the daily rainfall records of meteorological station managed by DHM in Nepal. These stations are primarily established to monitor various parameters, including river hydrology, water quality, sedimentation, limnology, snow hydrology, glaciology, weather, climate, agro-meteorology, air quality, and solar energy [37]. The cumulative sum of rainfall during the monsoon period (July – September) recorded by these stations are interpolated and assigned to the road section and utilized as an explanatory variable in the hazard model.

4.3.2Data Processing

Data preprocessing involves cleaning and organizing the datasets to ensure compatibility for analysis. The Markov deterioration hazard model has two assumptions which are outlined in Section 3.4. Road sections not satisfying Markov assumption and with missing traffic data or rainfall records are excluded to ensure consistency. The explanatory variables (e.g., AADT and CMR) are normalized to their maximum values to facilitate parameter and assigning rainfall data to road sections using spatial interpolation methods.

4.3.3 Rainfall Interpolation Techniques

Two interpolation techniques are used to distribute rainfall data spatially across the road network preprocessing involves cleaning and organizing the datasets to ensure compatibility for analysis.

4.3.3.1 Inverse Distance Weighted (IDW) interpolation.

The IDW interpolation method is a deterministic technique widely used to estimate unknown values at a given location based on nearby known values. These known values are weighted inversely by their distance from the target location, meaning that closer points have a stronger influence on the predicted value than distant points. To estimate the value at an unmeasured location, IDW utilizes the measured values surrounding the prediction location [34]. The generalized equation for IDW is:

$$Z(x_o) = \frac{\sum_{i=1}^{N} Z(x_i).d_i^{-p}}{\sum_{i=1}^{N} d_i^{-p}} \tag{4.1}$$

where:

$Z(x_o)$ = the interpolated value at the target location x_o.

$Z(x_i)$ = the known value at the i^{th} location.

d_i = the distance between the i^{th} known point and the target location x_o.

N = the number of known stations used for interpolation

p = the power parameter, which influences the weighting of known values. As the distance between the prediction location and the measured locations increases, the influence of each measured point on the prediction decreases exponentially.

4.3.3.2 Empirical Bayesian Kriging 3D (EBK3D) Interpolation.

EBK3D is a geostatistical interpolation method that extends kriging into three-dimensional space. The variogram in EBK3D characterizes the spatial dependency structure of the data, allowing the interpolation to consider both the distance and spatial correlation between points. A Bayesian framework is used to account for uncertainty in variogram estimation, enhancing the accuracy of the variogram estimates [33]. The generalized equation for EBK is:

$$Z(s_X) = \sum_{i=1}^{N} \lambda_i Z\,(s_i) \tag{4.2}$$

where:

$Z\,(s_i)$ = the measured value at the i^{th} location

$Z\,(s_X)$ = the interpolated value at a known location

N = the number of measured values

λ_i = the weights assigned to each known point. These weights are calculated by integrating information from semivariograms that are generated from the datasets. For the semivariograms, it is essential to compute the semi-variance using Equation (4). The details of which are explained in the following section.

The coordinates s_i and s_X represents 3D locations, i.e. (x, y, z). The semivariogram model is calculated in 3D, accounting for spatial autocorrelation in all three dimensions. The estimation involves calculating the distances in 3D space:

$$h_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{4.3}$$

where, h_{ij} represents the 3D distance between two s_i and s_j.

Semi-Variance

Semi-variance is a statistical measure of the dissimilarity between two spatial points separated by a certain distance. It quantifies how similar (or different) two points are based on their values. The general formula for semi variance is given by:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(s_i) - Z(s_i + h)]^2 \tag{4.4}$$

where:

$\gamma(h)$ = semi-variance for a given lag distance h.

$N(h)$ = number of pairs of points that are separated by a distance h.

$Z(s_i)$ = value at location s_i.

$Z(s_i + h)$ = value at a location separated from s_i by a distance h.

The lag distance (h) is the interval used to group point pairs for calculating semi-variance.

Semivariogram

A semivariogram is a plot of semi-variance (a measure of dissimilarity) on the y-axis and lag distance on the x-axis that shows how

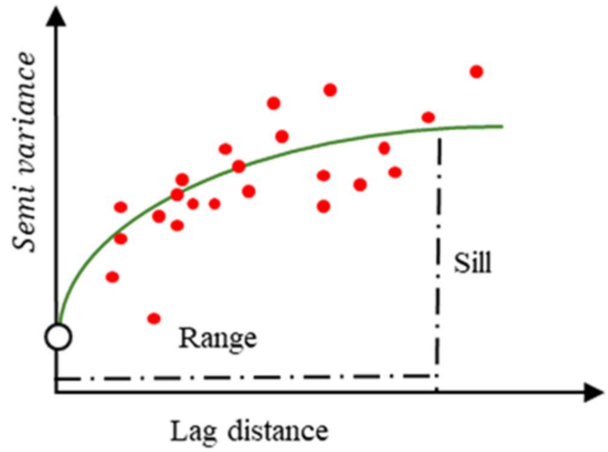

Figure 4.2.a A simple semivariogram.

the semi-variance between pairs of points changes with increasing distance. The semivariogram helps describe the spatial autocorrelation of a dataset, showing how related data points are based on their separation distance. It provides insights into how variability between data points changes with distance[35].

A simple semivariogram is shown in Figure-2. (a). The red dots (points) represent the calculated semivariance $\gamma(h)$ values corresponding to each lag distance h. The green curve represents the best-fit semivariogram. There are three components of a semivariogram.

1. Nugget (C_o): The value where the semivariogram intercepts the y-axis. This represents spatial variability at very small scales or measurement error.
2. Range (a): The distance beyond which points are no longer spatially correlated.
3. Sill (C): The value of the semi-variance at which the semivariogram levels off. This represents the point where adding more distance between points does not increase variability further.

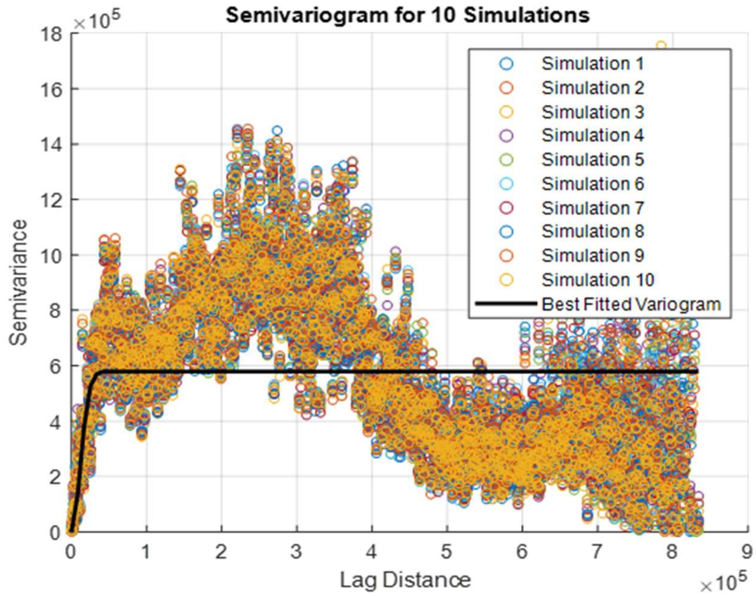

Figure 4.2.b The EBK model semivariograms.

Similarly, semivariogram modeling in the EBK method involves multiple simulations to form a variogram spectrum and the best fit variogram model is computed to determine the nugget, sill and range value. The prime advantage of EBK3D is that it automatically calculates these components through a process of sub-setting and simulations requiring minimal intervention [33]. Figure-2. (b). illustrates an example the of best-fit variogram model for rainfall data recorded by 422 rainfall stations all over Nepal in 2021. The values C_o, a and C derived from the EBK method using equation (4) are used to fit the theoretical exponential semivariogram model. This model estimates the semivariance value $\gamma(h)$ at lag distance h using the formula:

$$\gamma(h) = C_o + C\,(1 - e^{-\frac{3h}{a}}) \tag{4.5}$$

Referring to equation (2), to obtain the value for λ_i, we need to solve the linear system:

$$K \cdot \lambda_i = X \tag{4.6}$$

$$\begin{bmatrix} \gamma(h_{11}) & \gamma(h_{12}) & \cdots & \gamma(h_{1N}) & 1 \\ \gamma(h_{21}) & \gamma(h_{22}) & & \gamma(h_{2N}) & 1 \\ \vdots & \vdots & \ddots & \vdots & 1 \\ \vdots & \vdots & & \vdots & 1 \\ \gamma(h_{N1}) & \gamma(h_{N2}) & \cdots & \gamma(h_{NN}) & 1 \\ 1 & 1 & & 1 & 0 \end{bmatrix} * \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_N \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma(h_{1X}) \\ \gamma(h_{2X}) \\ \vdots \\ \vdots \\ \gamma(h_{NX}) \\ 1 \end{bmatrix} \quad (4.7)$$

In equation (6), K is the kriging matrix and each element $\gamma(h_{ij})$ is the semivariogram value between the two points i and j computed by using equation 5, such that $\gamma(h_{12}) = \gamma(h_{21})$ and $\gamma(h_{11}) = \gamma(h_{22}) = \gamma(h_{NN}) = \gamma(0) = 0$. The values for $\boldsymbol{\lambda_i}$ can be computed by rearranging equation (6) as $\lambda_i = K' \cdot X$.

Similarly, $[\lambda_1, \lambda_2, \ldots \lambda_N]$ are the weights assigned such that the value $[\lambda_1, \lambda_2, \ldots \lambda_N]$ will be between 0 and 1 and their sum will be 1. μ is the Lagrange multiplier used to ensure that the sum of weights is 1.

4.3.3.3 Error metrics and Comparision.

Error metrics are statistical measures used to evaluate the accuracy of a predictive model by quantifying the differences between observed O_i $(i = 1, 2, \ldots, n)$ and predicted P_i $(i = 1, 2, \ldots, n)$ values, where n is the number of the observation. Individual method prediction errors E_i are usually defined as $E_i = P_i - O_i$. Common error metrics used to compare between the methods are the following:

Mean Absolute Error (MAE)

MAE represents the average magnitude of errors between observed and predicted values, considering all differences without taking their direction into account. In simple terms, it tells us how far the model's predictions are from the actual values on average. The general formula for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E_i| \quad (4.8)$$

Lower MAE values indicate better model performance, meaning the model's predictions are closer to the observed values. Since MAE has the same units as the observed values, it is scale-dependent and is directly interpretable in the context of the data being evaluated [38].

Root Mean Square Error (RMSE)

RMSE measures the square root of the average squared differences between observed and predicted values. The general formula for RMSE is:

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}(E_i)^2 \tag{4.8}$$

RMSE gives more emphasis on larger errors by squaring the error. Lower value of RMSE indicate better model accuracy [38].

Mean Bias Error (MBE)

MBE represents the average difference between observed and predicted values, indicating the model's bias. The general formula for RMSE is:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(E_i) \tag{4.8}$$

A MBE value close to zero indicates little bias, whereas a positive or negative value suggests that the model tends to systematically overestimate or underestimate, respectively [38].

4.3.4 Markov deterioration hazard model formulation.

The Markov deterioration hazard model is a probabilistic model to predict the pavement condition transition based on survival analysis and hazard function. It assumes that : (a) during the inspection period no maintenance activities were carried out and no measurement error occurred and (b) the deterioration of the road infrastructure is a natural process and its condition gradually degrades over time [13].

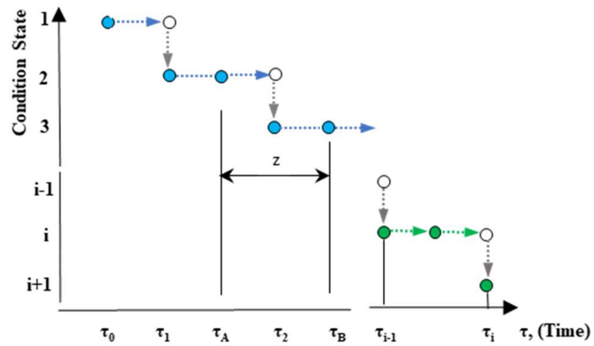

Figure 4.3 Periodic inspection of condition states.

The road infrastructure deterioration process and periodic inspection of condition states are illustrated graphically in Figure-3. Here, the y-axis is real calendar time (in short, time) denoted by the symbol τ. The deterioration of the road pavement starts immediately after the construction is completed and the road is opened to traffic at an initial time τ_0. The condition state of a pavement section is expressed by a rank J representing a state variable i $(i = 1, 2, \dots, J)$. For a new pavement $i = 1$ and the state variable j is assumed to increase as deterioration progresses. A value of $i = J$ indicates that a pavement section has reached the end of its service life.

The information corresponding to the deterioration process of a pavement can be obtained from periodic inspections. For simplicity two periodic inspections are conducted at time τ_A and τ_B, at a time interval of z. It is supposed that at time τ_A the condition state observed during the inspection is i $(i = 1, 2, \dots, J-1)$. It is difficult to obtain information about the time at which the transition to the observed condition state occurred i.e. τ_1 and τ_2. The transition process of the condition state for road pavement is uncertain and forecasting future condition state cannot be determined deterministically. Assuming that the deterioration process follows the Markov chain, the Markov transition probability (MTP) is employed to represent the uncertainty in condition state transitions over two time points. In other words, MTP is utilized to predict pavement deterioration based on the periodic inspection process as illustrated in Figure-3.

Let us suppose that during periodic inspection at time τ_A, the observed condition state of the road pavement is i. This is represented by the condition state variable $h(\tau_A) = i$. Then the Markov transition probability π_{ij} is defined as the probability that given a condition state $h(\tau_A) = i$ observed at time τ_A will transition to $h(\tau_B) = j$ at a future time τ_B. Mathematically it is expressed as:

$$\text{Prob}[h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \tag{4.8}$$

By deriving the pair of states (i, j) from a transition probability we can obtain the MTP matrix $\prod$, which is expressed as:

$$\prod = \left(\begin{bmatrix} \pi_{11} & \cdots & \pi_{1J} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{bmatrix} \right) \tag{4.8}$$

Regarding the MTP, the following must hold true:

$$\pi_{ij} \geq 0 \ (i, j = 1, \dots, j)$$

$$\pi_{ij} = 0 \text{ (when } i > j\text{) and}$$

$$\sum_{j=1}^{J} \pi_{ij} = 1$$

The condition state J is the absorbing state in the Markov chain if there is no repair, thus $\pi_{JJ} = 1$ is true. Moreover, the MTP is independent of past deterioration records and is dependent only on the condition state at the time of inspection.

4.3.4.1 Estimation of MTP.

The MTP based on the exponential hazard model are defined in the following equations.

$$\pi_{i\,i} = \text{Prob}[h(y_B) \; = \; i \mid h(y_A) \; = \; i] = \exp(-\theta_i Z) \tag{4.13}$$

$$\pi_{i\,i+1} = \text{Prob}[h(y_B) \; = \; i+1 \mid h(y_A) \; = \; i]$$

$$= \frac{\theta_i}{\theta_i - \theta_{i+1}}\{-\exp(-\theta_i Z) + \exp(-\theta_{i+1} Z)\} \tag{4.14}$$

$$\pi_{ij} = \text{Prob}[h(y_B) \; = \; j \mid h(y_A) \; = \; i]$$

$$= \sum_{k=i}^{j}\prod_{m=i}^{k-1}\frac{\theta_m}{\theta_m - \theta_k}\prod_{m=k}^{j-1}\frac{\theta_m}{\theta_{m+1} - \theta_k}\exp(-\theta_k Z) \tag{4.15}$$

where

$$\prod_{m=i}^{k-1}\frac{\theta_m}{\theta_m - \theta_k} = 1, at\ (k \leq i+1)\ and$$

$$\prod_{m=k}^{j-1}\frac{\theta_m}{\theta_{m+1} - \theta_k} = 1\ at\ (k \geq j).$$

In equation (15) , π_{ij} $[0 < \pi_{ij} < 1]$, and π_{iJ} is structured according to the MTP conditions as follows:

$$\pi_{iJ} = 1 - \sum_{j=1}^{j-1}\pi_{ij} \tag{4.16}$$

Equation (13 - 16) defines the multistage exponential hazard model. In this model, the hazard rate $\theta_i^k(i = 1, 2, \ldots ,\ J-1); k = 1, \ldots, K)$ representing the deterioration process of a road pavement section is considered to change in relation to explanatory variables $\mathbf{x^k}$ as follows:

$$\theta_i^k = exp(\boldsymbol{\beta_{i,1}} + \boldsymbol{\beta_{i,2}}\boldsymbol{x_2^k} + \ldots, \boldsymbol{\beta_{i,M}}\boldsymbol{x_M^k}) \tag{4.17}$$

$$\theta_i^k = \ f(\boldsymbol{x^k}\colon \boldsymbol{\beta_i'}) \tag{4.18}$$

Where $\beta_i = (\beta_{i,1,} \ldots, \beta_{i,M})$ is a row vector of unknown parameters, $\beta_{i,m} = (m = 1, \ldots, M)$ and the symbol ‘ indicates the vector s transpose.
Briefly, the elements of MTP matrix π_{iJ} are estimated using dataset $\pi_{iJ}\,(Z^k, \boldsymbol{x^k}: \boldsymbol{\beta_i})$ which can be obtained from inspection. The unknown parameter $\boldsymbol{\beta_i}\,(i = 1, 2, \ldots, J-1)$ is determined using the Bayesian estimation method. For a detailed explanation of the Bayesian method for estimation it is recommended to refer to Han D et al. [17]. Using equation (18) the hazard function θ_i^k is estimated.
By using the obtained hazard function the life expectancy (LE) of each condition state i is then defined by means of survival function $R_i(y_i^k)$. [39]

$$LE_i^k = \int_0^{\infty} \exp\left(-\theta_i^k y_i^k\right) dy_i^k = \frac{1}{\theta_i^k} \tag{4.19}$$

$$LE_i^J = \sum_{i=1}^{J-1} LE_i^k \tag{4.20}$$

The life expectancy from condition state i to J can be defined by the sum of life expectancies, and the deterioration curve can be attained by their relations. The MTP matrix $\prod$ as described in equation (12) is derived by combining π_{ij} from equation (13 – 16). For more details, it is suggested to refer to Tsuda et al., 2006 [13].

4.4 Empirical Analysis.

For this empirical analysis the actual pavement inspection data for national highway road surfaces from DOR were employed. DOR currently manages 14,913 km of SRN and 2,025 no. of motorable bridges. This excludes approximately 3,029 km of highways that are either under construction or planned [5,6]. Based on the pavement type these road network can be classified into two groups (i) surface treatment over granular base (STGB) and (ii) asphalt material over granular base (AMGB). In the annual road condition survey conducted in 2022, it was found that 88.45 percent of Nepal's national highways are paved with STGB pavement. STGB is simple, highly effective and cost-efficient road surface treatment, provided that proper planning and execution of the work are followed during the construction [40].

The SDI data for national highways with STGB pavement, collected from the annual pavement inspection surveys for the years 2021 and 2022, were used in this study. The data set confirms the assumptions of the Markov model were analyzed. A Bayesian estimation for the Markov deterioration hazard model was performed utilizing the actual inspection data sets, all based on SDI and each spanning 1 km. The inspection data consist of two condition states—an initial and a final state—as defined in Table 4.1. These states serve as performance measures of road pavement distress, derived from two inspections conducted at specific intervals, denoted as Z, with explanatory variables, denoted as x.

In this study monsoon rainfall is considered as the explanatory variable and is acquires from the daily records from DHM. DHM has established 579 meteorological stations and 110 hydrological stations to monitor all hydrological and meteorological activities across Nepal. To implement the Bayesian estimation for the Markov deterioration hazard model, the condition ratings presented in Table 1 were used to evaluate the pavement conditions based on the SDI values. Condition state 1 represents the best condition, while condition state 6 indicates the worst pavement condition.

In this study, CMR is considered as an environmental explanatory variables. This is the sum of daily rainfall during the monsoon period. These values are interpolated using two interpolation techniques: IDW and EBK3D. Equation (1) is used with a power parameter (p) set to 2 for performing the IDW interpolation. A total of 422 of the 579 meteorological stations, each with a complete record of monsoon rainfall, are randomly divided into training and validation sets, containing 80 percent and 20 percent of the data, respectively. The CMR data from the training set of stations are used for interpolation and to determine the distribution of CMR over Nepal using the IDW and EBK3D methods. The CMR values at the validation set of stations are then predicted and compared with the actual measured values using error metrics. Lower value of MAE, RMSE and MBE indicate that EBK3D, which incorporates spatial correlations in three dimensions, provides higher interpolation accuracy compared to IDW. Consequently, the interpolated CMR values obtained through the EBK3D method were utilized as an explanatory variable in the Markov deterioration hazard model.

Table 4.1 Road condition based on SDI

SDI Value	Condition	Incidence of minor defects	Incidence of major defects	Condition State	SDI Value
0	Good	None	None	1	0
1	Moderate	1 to 200 sq.m. per km.	1 occurrence	2	1
2	Satisfactory	< 50% of the area	2 to 4 occurrences	3	2
3	Fair	≥ 50%	< 30% of area	4	3
4	Poor	-	30% or potholes and base exposed < 20% of the area	5	4
5	Bad	-	Potholes and exposed base = 20% of the area	6	5

The interpolated values are assigned to the road sections and the data set $DS = [i, j, z, aadt, C_{m,EBK3D}]$ is prepared. Dataset for which information on traffic and CMR are not available were removed. The final database used for exponential hazard model estimation consisted of 5,757 samples for DS. Furthermore, the explanatory variables were normalized to their maximum value to facilitate the estimation procedure. These datasets are utilized in this study to estimate the unknown parameter $\boldsymbol{\beta}$, hazard rate, and life expectancies for each transition in condition state using equation (17-20). Additionally, the pavement deterioration curve can be plotted to visually understand the deterioration process.

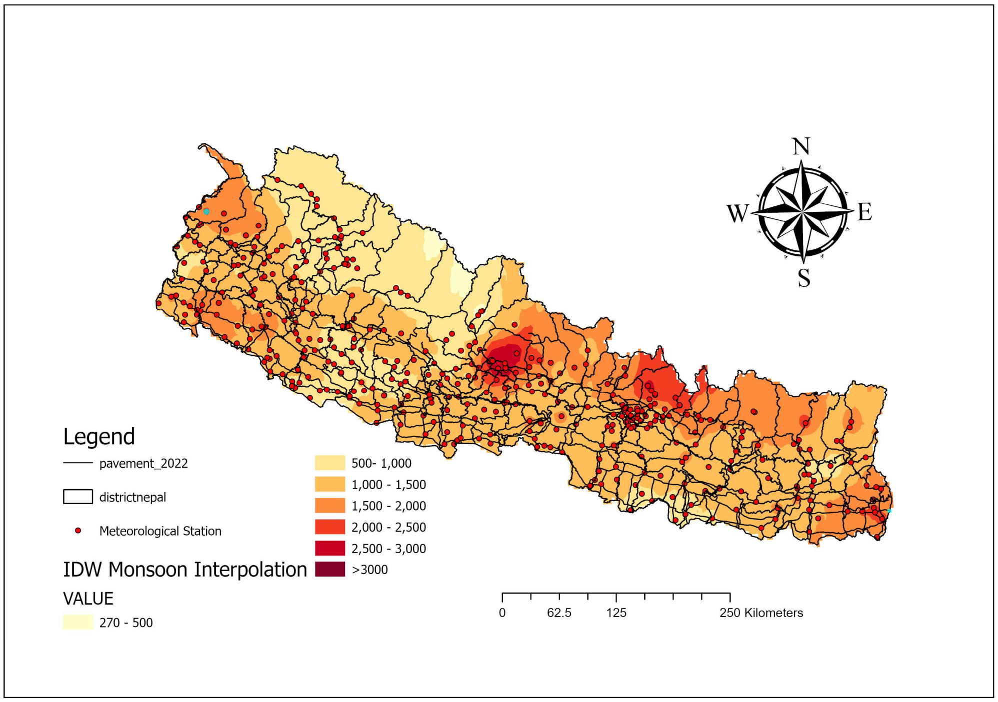

Figure 4.4.a SRN and CMR Distribution using IDW, mm, 2021.

4.5 Results.

The cumulative monsoon rainfall distribution for Nepal was generated using IDW and EBK3D interpolation with 2021 rainfall data, as depicted in Figure-4.4.a and 4.4.b respectively. The result for the error metrics are shown in Table 4.2.

Table 4.2 Error metric values

S.No	Method	MAE	RMSE	MBE
1	IDW	454.66	616.57	145.95
2	EBK3D	421.90	588.32	121.17

Comparing the two interpolation methods, the lower values of MAE and RMSE for EBK3D indicate higher accuracy, and the lower value of MBE indicates minimal bias.

The interpolated value from the EBK3D interpolation method was assigned to the road sections as the explanatory variable. With the dataset

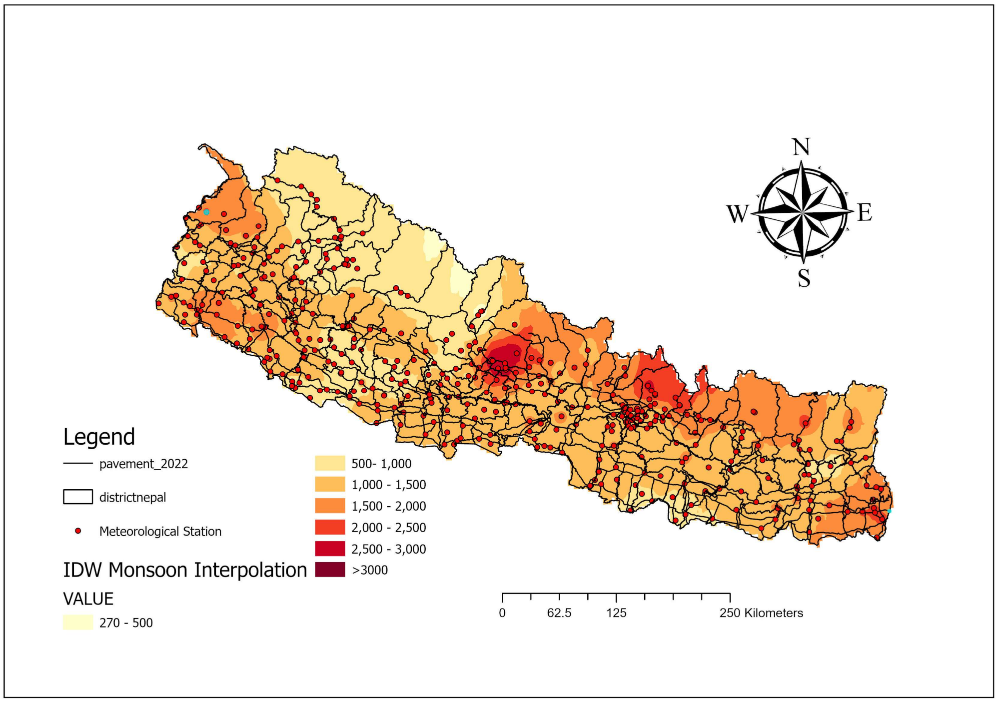

Figure 4.4.a SRN and CMR Distribution using IDW, mm, 2021.

structured as DS the exponential hazard function was estimated separately. MTP matrixes for each sample is estimated using equation (13-16). The average MTP matrix was determined in order to avoid the huge amount of individual estimations and is presented in Table 4.3. Since there is one exponential hazard function for each of the five ratings and each equation contains three unknown parameters, there are 15 unknown parameters $\boldsymbol{\beta} = \{\boldsymbol{\beta}_{i1}, \boldsymbol{\beta}_{i1}, \boldsymbol{\beta}_{i1}\ (i = 1, \dots, 5)\}$. Positive values of the unknown parameter $\boldsymbol{\beta}$ for the explanatory variable indicate a positive deteriorating effect on the pavement. For the data sets DS, the Bayesian estimates of the unknown parameter $\boldsymbol{\beta}$ are presented in Table 4.4. with each explanatory variable's corresponding Geweke's test value shown in parenthesis.

The expected hazard rate is obtained through equation (18) which is defined using the exponential hazard function for the dataset mentioned above. The life expectancy of a rating, indicating the elapsed time in reaching the next rating is obtained using equation (19). The effect of CMR on deterioration speed is analyzed for minimum and maximum level of the explanatory variable. The expected deterioration path can be represented by a graph describing the average deterioration process during the life expectancy of the rating (from the time the rating is reached to the time the next rating is attained). The expected deterioration path of pavement for monsoon using EBK3D interpolation is illustrated in Figure-5.

Table 4.3 MTP Matrix – Model$_{EBK3D}$

Rating	1	2	3	4	5	6
1	0.288	0.297	0.319	0.076	0.017	0.004
2	-	0.195	0.539	0.192	0.057	0.018
3	-	-	0.515	0.306	0.126	0.053
4	-	-	-	0.411	0.346	0.243
5	-	-	-	-	0.368	0.632
6	-	-	-	-	-	1.000

Table 4.4 MTP Matrix – Model$_{EBK3D}$

Rating	Absolute Term, β_0	AADT, β_{i1}	CMR, β_{i2}
1-2	0.718	0.195	-
	(-1.116)	(1.558)	-
2-3	0.618	1.043	-
	(1.287)	(0.890)	-
3-4	-0.704	-	0.869
	(-1.021)	-	(1.734)
4-5	-0.255	-	0.443
	(1.011)	-	(-1.069)
5-6	0.412	-	-
	(0.692)	-	-

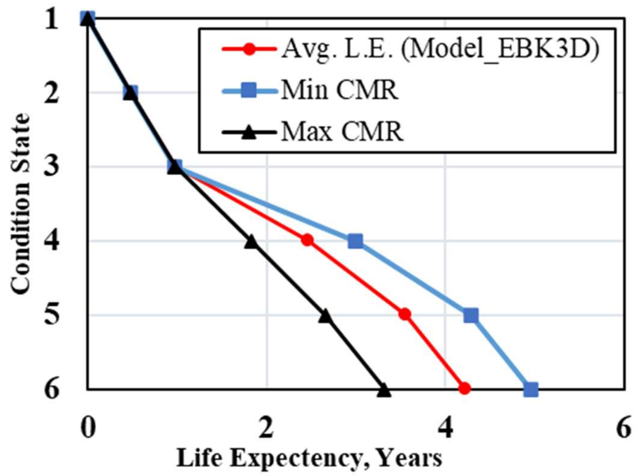

Figure 4.5 Expected deterioration path for monsoon using EBK3D.

The findings indicates that both traffic and environmental factor i.e. CMR in this study significantly contributes to pavement deterioration. The deterioration process is modeled using the positive values of the unknown parameter $\boldsymbol{\beta}$ for AADT and CMR. With EBK3D interpolation, the average pavement life expectancy is estimated at 4.22 years, incorporating AADT and CMR as explanatory variables. In Figure 5.5, the effect of monsoon indicates there is a significant reduction of 38.75% of the service life which is acceptable and justifiable.

4.6 Discussion

The results show the significant impact of traffic and environmental factors on road pavement deteriorations. Referring to Table 4.4, the estimated value of $\boldsymbol{\beta}_{i1}$ for the traffic parameter shows the deterioration action on the pavement till the pavement is in satisfactory condition. This deterioration process is relatable to the real-world conditions. The negative values of $\boldsymbol{\beta}_{i1}$ for the fair, poor and bad conditions indicate that with the increase in traffic the condition of the pavement will be improved, which is not acceptable, hence these values are excluded from the pavement deterioration model. Similarly, the estimated value of $\boldsymbol{\beta}_{i2}$ for the environmental parameter, i.e., CMR expressed in mm, indicates accelerated deterioration on the pavement in the satisfactory, fair and poor condition states. This can be interpreted as when the pavement surface is in a good to satisfactory condition the monsoon rain will safely drained off the pavement surface which will not trigger the bituminous pavement failure mechanism. The average deterioration rate and the average life expectancies (in years) for different condition state are known. This information offers a practical time frame for planning efficient inspection intervals and maintenance strategies. From this study the effect of monsoon is estimated in Figure-5 for different condition states and the results show that the monsoon factor contributes to a significant 38.75% reduction of pavement service life.

In the context of DOR, periodic maintenance, along with combined maintenance activities, is carried out to keep the pavement in fair to good condition and prolong the life expectancy of the pavement. From the study, referring to Figure-5, the average life expectancy of bituminous pavement in Nepal is 4.22 years. If we assume that after periodic maintenance the pavement will be reinstated to the best condition state i.e. condition state 1, then under the action of traffic, and monsoon it will deteriorate and reach its absorbing state (J) in approximately 4 years. From this, it can be inferred that the current practice of periodic maintenance for resealing bituminous pavement at intervals of 5 to 8 years regardless of pavement deterioration rate, may be too long for roads exposed to high monsoon. As a result, the pavement may reach a condition state that cannot be restored to a good condition through periodic maintenance alone, ultimately requiring more costly maintenance solutions like rehabilitation or reconstruction [11].

Referring to Figure-5, the average pavement deterioration curves indicate that the pavement deterioration rate for Nepal is high considering the traffic and environmental factor. The current practice of reactive maintenance may not be sufficient for extending the service life of the pavement and reducing the life cycle cost in the long-term. The introduction of preventive maintenance strategy to supplement periodic maintenance could be an effective approach for bituminous pavement with higher CMR, where periodic maintenance alone may not restore the pavement to the expected good condition.

4.7 Conclusion

This research presents a comprehensive approach for integrating environmental data into pavement deterioration modeling using Markov deterioration hazard models. The key achievements of this study are as follows:

1. Integrating monsoon rainfall effects on pavement performance in Nepal: a Markov deterioration model is presented using SDI and incorporating monsoon rainfall as a key environmental factor.
2. Comparison of interpolation methods for rainfall estimation: by comparing the IDW and EBK3D interpolation techniques, we found that the EBK3D method provided a more accurate value for CMR, as supported by the lower MAE, RMSE and MBE value.
3. Quantification of CMR on pavement deterioration: the study found that CMR accelerates pavement deterioration, reducing service life by approximately 38.75% in Nepal, and suggests better maintenance planning before and after the monsoon.
4. Practical Implications for road asset management: The findings demonstrate that geostatistical methods capable of accounting for spatial dependency, such as EBK3D, can enhance the accuracy of models that incorporate environmental factors like monsoon. These results suggest that road agencies like DOR should consider using more advanced interpolation methods like EBK3D when developing predictive models for pavement management, particularly in regions where environmental variables play a critical role in pavement performance.

While this study provides valuable insights into pavement deterioration modeling using a Markov hazard framework with environmental data, there are some limitations to consider. First, the accuracy of the model heavily relies on the quality of the input data. In this study, CMR data were the sum of daily monsoon values from June –

September, however, the monsoon period may vary. Any inaccuracies due to early or delayed monsoon can give inaccurate value which may affect the interpolation and model performance. Second, this study considered only cumulative monsoon rainfall as the environmental factor. Although rainfall is a critical factor, other environmental variables such as temperature fluctuations, freeze-thaw cycles, and soil type may also contribute significantly to pavement deterioration.

However, future studies can enhance the model by including other environmental and climatic factors such as temperature, freeze-thaw cycles, and humidity. This would provide a more comprehensive understanding of how different environmental conditions jointly affect pavement deterioration. Expanding the model to incorporate these variables could lead to improved predictions and more effective pavement management strategies.

The model can also be checked for different types of pavements (e.g., rigid, composite) and different regions of Nepal (e.g., plains, hills, and mountains) to evaluate its applicability and effectiveness in various contexts. Testing the model to varied topographies and pavement types will help in understanding how local conditions influence the deterioration process and will support the development of region-specific maintenance guidelines. These enhancements will contribute to more comprehensive pavement deterioration models, supporting infrastructure planning and resource allocation for effective road asset management.

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Chapter 5 : Multi-Dimensional Pavement Degradation Framework for Highway Maintenance Planning

5.1 Introduction

Efficient pavement repair is advocated to extend the service life of pavements for which the introduction of preventive maintenance strategies is important. In the maintenance and management of highway pavements, it is necessary to consider the performance of pavements in terms of safety and driving comfort. So road managers should develop new and improve existing strategies to better pavement condition. The road surface condition indices including cracking rate, rutting depth, and International Roughness Index (IRI), are regularly obtained through road condition surveys. Pavement condition inspection data can be used to estimate deterioration rates and develop plans for maintenance, repair and rehabilitation of highway pavements. In addition, pavement sub-surface conditions may be known through estimating the deflection rate using the Falling Weight Deflectometer (FWD). The FWD survey can be used to estimate pavement load-bearing capacity by measuring its deflection rate at specific locations. [1] lists important considerations for road service that include comfort and safety.

In road asset management, research on statistical deterioration prediction using inspection data including visual surveys and load bearing capacity has been accumulated. The Markov deterioration hazard model developed by Tsuda et al. (2006) has been advanced into different statistical deterioration prediction models that can be used under various conditions [2]. For example, the Markov hazard model was improved to the mixed Markov deterioration hazard model that enables quantification of heterogeneity for each evaluation unit set by administrators [3]. Lethanh and Adey (2012) developed a hidden Markov model to model pavement deterioration in case of incomplete monitoring data for pavement processes that are not directly measurable [4]. In this study, pavement deterioration is modeled as an aggregation of several degradation processes estimated using continuous quantities.

The indicators of pavement deterioration are often expressed as continuous quantities, such as road surface roughness and load bearing capacity. These continuous quantities can be discretized into state categories used as inputs in conventional Markov models. The continuous quantity deterioration hazard model can be applied directly without discretizing continuous quantities into condition states [5]. The developed model can be used to evaluate individual deterioration events after structural health monitoring, and to correlate the heterogeneity within each deterioration event applying a mixed Markov deterioration hazard model [6].

Conventional Markov models apply a single or discrete indicator such as surface soundness and do not represent the deterioration process considering the dependency structure of multiple continuous deterioration processes. Additionally, past models do not elaborately describe the deterioration process considering interdependence and the relationships among multiple degrading events. This study proposes a methodology for modeling the entire deterioration process described using multiple continuous quantity indices comprehensively.

The deterioration process for each deterioration index is modeled as a continuous quantity deterioration process that takes heterogeneity into account, and the correlation structure among multiple indices is described using copulas. By using the methodology proposed in this study, deterioration process benchmarking for multiple events using continuous quantities can be achieved which positively impacts maintenance planning. The proposed methodology simultaneously takes into consideration the temporal evolution of multiple deterioration events. The model estimation results are useful for the prediction of multi-dimensional deterioration of infrastructure facilities for the development of maintenance, repair and rehabilitation strategies that account for the characteristics of multiple deterioration events.

The rest of the paper is organized as follows. The next section describes the research methodology followed by a description of the basic concept of the study. The subsequent section details the proposed multidimensional deterioration process model using continuous quantities and expression of the correlation among deterioration events using copulas. Lastly, the applicability of the multidimensional deterioration process model using continuous quantities is demonstrated through a case study on highway pavements and the conclusion and future research work are stated.

5.2 Basic Concept of this Study

5.2.1 Multi-dimensional Evaluation of Structural Deterioration Rate

Prior studies have been conducted to express the deterioration process of structures based on a single structural health monitoring index. For instance, in the case of pavements, the following two approaches are often adopted; i.e., (1) aggregation of individual distresses such as cracking, rutting, and roughness into a single evaluation index coupled with modeling the temporal change of this aggregated index and (2) modeling the change of each distress index mentioned over time. However, because of the variety of deterioration factors involved in the deterioration process of infrastructures, the following two conditions are often observed; i.e, (i) a single deterioration process may dominate and/or (ii) multiple deterioration events may interact with each other and jointly influence the rate of deterioration progression.

Inspection data for a single deterioration process may not be sufficient to model the entire infrastructure deterioration progression. Moreover, the inspection data observed in reality contains a mixture of such multiple cases. For this reason, when using data synthesized as a single indicator, it is difficult to determine which indicator best represents the deterioration process. In addition, the deterioration process model using a single deterioration event does not provide information on the heterogeneity of deterioration processes for each infrastructure facility and the correlation between deterioration events.

The multi-dimensional deterioration process model proposed in this study is applicable to the case where the deterioration management index of a structure is expressed as a continuous quantity and takes into account the heterogeneity of the deterioration processes in question. The continuous deterioration hazard model uses a baseline model as a benchmark case. The heterogeneity of the category is represented by the heterogeneity parameter ε that is distributed according to a probability density function $p(\varepsilon)$ which makes it possible to evaluate the relative deterioration rates of individual structure categories. $\varepsilon = 0$ corresponds to the benchmark, while $\varepsilon > 0$ is a structure that deteriorates relatively faster than the benchmark, and $\varepsilon < 0$ is a structure that deteriorates relatively slower than the benchmark.

5.2.2 Modeling the Correlation Structure Using Copulas

When evaluating the deterioration rate of infrastructure facilities using multiple deterioration management indices, the heterogeneity parameter, which represents the heterogeneity of the deterioration rate for each degradation process may show the correlation between the processes. In this study, multivariate copulas are used to express the dependency structure among event multivariate marginal distributions (see e.g., [7] for the use of copulas). The copulas are used to merge the marginal distribution functions of multiple random variables with their joint distribution functions. This study is unique in that joint distribution functions can be

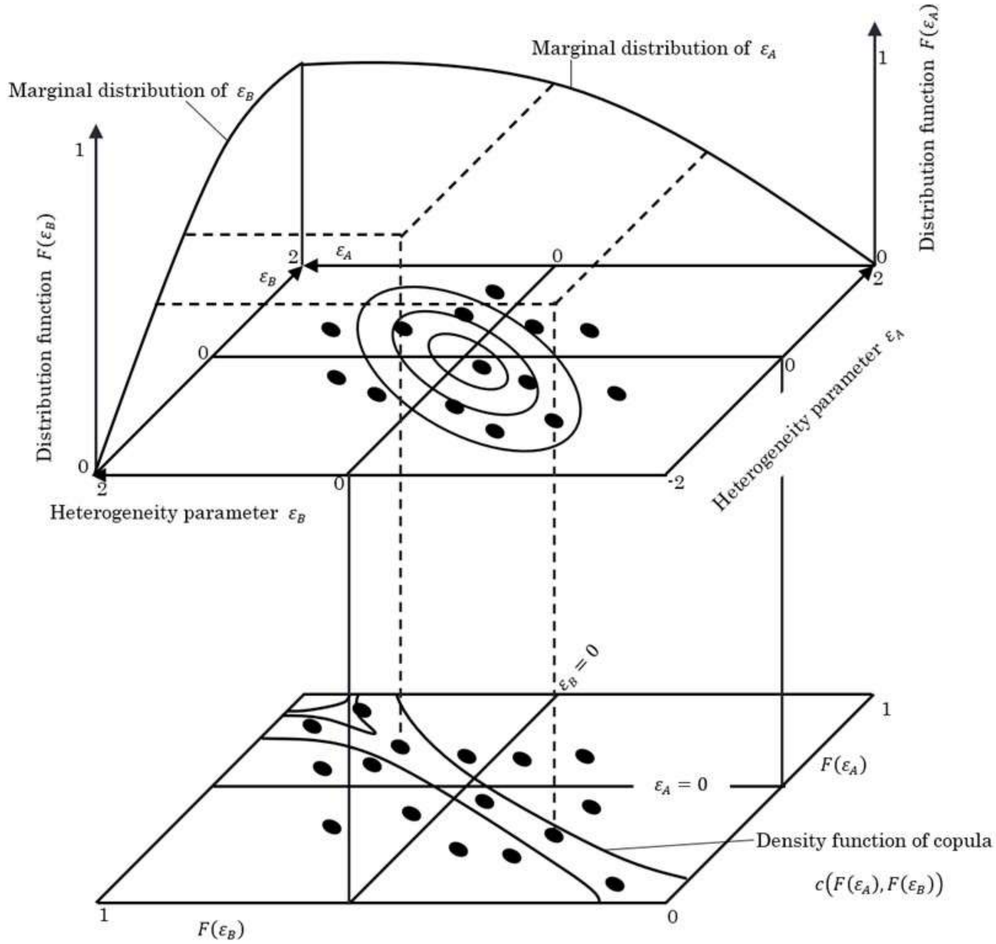

Figure 5.1 Joint distribution of heterogeneity parameters and copula

estimated while maintaining the probability structure of the multivariate marginal distributions.

Consider a case in which two types of deterioration events, A and B, are used to evaluate the deterioration state of multiple infrastructure facilities. The relationship between copulas, heterogeneity, marginal and joint distributions of parameters is shown schematically in the three-dimensional space (Figure 5.1). The vertical planes in Figure 5.1 show the marginal distribution functions of each heterogeneity parameter, allowing for relative evaluation of the deterioration rate of each event. The upper horizontal plane in Figure 5.1 shows the joint distribution of the heterogeneity parameter pairs (ε_A, ε_B) plotted in a two-dimensional space.

The information on the spatial distribution state of the heterogeneity parameters provides transition trends based on correlations among the heterogeneity parameters, as well as deterioration rates for individual deterioration events. For example, if two types of deterioration events are considered, the total deterioration rate for the two types of events can be expressed in terms of the rate of deterioration of each event. Additionally, in the two-dimensional space for two types of deterioration events, the deterioration characteristics of a structure can be classified into four categories in each quadrant. In the first quadrant ($\varepsilon_A > 0$ and $\varepsilon_B > 0$), the two deterioration events are both relatively faster than in the benchmark case. The second ($\varepsilon_A > 0$ and $\varepsilon_B < 0$) and fourth ($\varepsilon_A < 0$) and $\varepsilon_B > 0$) quadrants correspond to the progression of either deterioration events A or B is superior to that of the benchmarking case, while the other is inferior, respectively. The third ($\varepsilon_A < 0$ and $\varepsilon_B < 0$) quadrant can be evaluated as the progression of both events being slower than that of the benchmarking case. Moreover, the conditional probability density of a heterogeneity parameter, given that the other heterogeneity parameter is known, can be calculated using a copula and marginal distributions of the heterogeneity parameters as shown in the lower horizontal plane in Figure 5.1.

5.3 Multi-dimensional Deterioration Process Model with Continuous Quantities

5.3.1 Continuous Quantity Deterioration Hazard Model

For each multidimensional deterioration event d ($d = 1, \ldots, D$), the deterioration management index of facility i ($i = 1, \ldots, I$) is denoted as x_d^i and the elapsed time since the most recent construction (renewal) as t^i. The more the deterioration progresses, the larger the value of the deterioration indicator becomes. The progression of the deterioration process is formulated as

$$x_d^i = \exp\left(-B_d^i\right) f_d\,(t^i, \beta_d) \tag{5.1-a}$$

$$B_d^i = z^i \theta_d' - \varepsilon_d^k + \sigma_d w_d^i \tag{5.1-b}$$

where B_d^i is the deterioration characteristic coefficient of facility i, which can be expressed using the characteristic variable term $z^i \theta_d'$, the heterogeneity term ε_d^k and the error term $\sigma_d w_d^i$ as shown in Eq. (5.1-b). In Eq. (5.1-b), $z^i = (z^{i,1}, \dots, z^{i,M})$ is the characteristic variable vector affecting the deterioration of facility i, $\theta_d = (\theta_d^1, \dots, \theta_d^M)$ is the characteristic parameter vector, ε_d^k is the heterogeneity parameter expressing the unique deterioration rate in the group k $(k = 1, \dots, K)$ to which facility i belongs, w_d^i is the random error term expressing the deterioration factor unique to facility i, and σ_d is the deviation parameter. The heterogeneity parameter ε_d^k is assumed to follow a normal distribution with mean 0 and variance ϕ_d^2. Also, $f_d\left(t^i, \beta_d\right)$ is a deterioration model that represents the baseline deterioration process (hereafter, the baseline model) and is a monotonically increasing function with respect to t^i. Also, $\beta_d = (\beta_d^1, \dots, \beta_d^N)$ is the unknown parameter vector that characterizes the baseline model. If $exp(-B_d^1) = 1$ holds, the deterioration curve is identical to the baseline model. If the theoretical deterioration curve can be derived from a kinematic model, then it can be used as the baseline model. If no theoretical model exists, it is necessary to approximate the baseline model using, for example, a flexible function.

By taking the logarithm on both sides of Eq. (5.1-a),

$$\begin{aligned} y_d^i &= lnf_d\left(t^i, \beta_d\right) \\ &= lnx_d' + z_d^i \theta_d^i - \varepsilon_d^i + \sigma_d w_d^i \end{aligned} \tag{5.2}$$

is obtained where $y_d^i = lnf_d\left(t^i, \beta_d\right)$ is the non-linearized lifetime index. The stochastic error term w_d^i is assumed to follow the probability density function of the standard Gumbel distribution expressed as

$$g_w(w_d^i) = exp\{-w_d^i - exp(-w_d^i)\} \tag{5.3}$$

Where $\mathrm{E}(w_d^i) = \gamma = 0.57722 \ldots$ is an Euler constant.

Rewrite Eq.(5.2) as

$$w_d^i = \frac{y_d^i - lnx_d^i - z^i\theta_d' + \varepsilon_d^k}{\sigma_d} \tag{5.4}$$

and perform a variable transformation of the probability density function Eq. (5.3). As a result, the probability density function representing the conditional distribution of the lifetime index y_d^i until the deterioration management index value x_d^i is reached for facility i with deterioration characteristic z^i is expressed as

$$q_y(y_d^i|x_d^i, z_d^i) = \frac{1}{\sigma_d} g_w\left(\frac{y_d^i - lnx_d^i - z^i\theta_d' + \varepsilon_d^i}{\sigma_d}\right) \tag{5.4}$$

$$= \frac{1}{\sigma_d} exp\left\{-exp\left(-\frac{y_d^i - lnx_d^i - z^i\theta_d' + \varepsilon_d^i}{\sigma_d}\right)\right. \tag{5.5}$$

$$\left. - \frac{y_d^i - lnx_d^i - z^i\theta_d' + \varepsilon_d^i}{\sigma_d}\right\}$$

The

lifetime index $y_d^i = lnf_d(t^i, \beta_d)$ contains an unknown parameter β_d. If we denote the first derivative of the lifetime index as $\dot{f}_d(t^i, \beta_d) = df_d(t^i, \beta_d)/dt^i$, then

$$dy_d^i = \frac{\dot{f}_d(t^i, \beta_d)}{f_d(t^i, \beta_d)} dt^i \tag{5.6}$$

is satisfied. Thus, the probability density function representing the conditional distribution of real life t_i until the control level x_d^i is reached is

$$\tau\left(t^i \middle| x_d^i, z^i\right) \tag{5.7}$$
$$= \frac{\dot{f}_d\left(t^i\right)}{\sigma_d f_d\left(t^i\right)} exp\left\{-exp\left(-\frac{lnf_d(t^i) - lnx_d^i - z^i\theta_d' + \varepsilon_d^k}{\sigma_d}\right) - \frac{lnf_d(t^i) - lnx_d^i - z^i\theta_d' + \varepsilon_d^k}{\sigma_d}\right\}$$

From Eq. (5.3), the survival function is expressed as

$$S_w(w_d^i) = 1 - \int_{-\infty}^{w_d^i} g_w(w_d^i)\, dw \tag{5.8}$$

$$= 1 - \exp\{-\exp(\, g_w(-w_d^i)\}$$

Table 5.1 Selected Archimedian copulas

Copula	Generating function $\boldsymbol{\zeta}(u_d)$	Distribution function $C(u_1,\ldots,u_D)$	Probability density function $C(u_1,\ldots,u_D) = \frac{\partial^D C(u_1,\ldots,u_D)}{\partial u_1 \ldots, \partial u_D}$
Gumbel $\alpha \in (0, 1)$	$(-\ln \mathrm{u_d})^\alpha$	$\exp[-\{\sum_{d=1}^{D}(-\ln \mathrm{u_d})^\alpha\}^{1/\alpha}$	Partial differentiation of the distribution function; $\alpha \in (1, \infty)$; no general form
Clayton $\alpha \in (0, \infty)$	$\frac{1}{\alpha}(u_d^{-\alpha} - 1)$	$\sum_{d=1}^{D}\{u_d^{-\alpha} - D + 1\}^{-1/\alpha}$	$\{\prod_{d=1}^{D-1}(1 + d\alpha)\}(\prod_{d=1}^{D-1}(u_d^{-\alpha-1}))$. $(\sum_{d=1}^{D} u_d^{-\alpha} - D + 1)^{-1/\alpha - \mathrm{D}}$
Frank $\alpha \in (0, \infty)$	$\ln\{(\exp(-\alpha\, \mathrm{u_d}) - 1\} - \ln\{(\exp(-\alpha - 1\}$	$-\frac{1}{\alpha}\ln\left[1 + \frac{\prod_{d=1}^{D-1}\{exp(-\alpha\, u_d) - 1\}}{\{exp(-\alpha) - 1\}^{D-1}}\right]$	Partial differentiation of the distribution function; $\alpha \in (0, \infty)$; no general form

For a facility i with deterioration characteristic z^i, the probability that the deterioration control index value has not reached x_d^i when the lifetime index y_d^i has passed can be expressed using the survival function

$$S_w(\, y_d^i | x_d^i, z^i) = S_w\left(\frac{y_d^i - lnx_d^i - z^i\theta_d' + \varepsilon_d^i}{\sigma_d}\right)$$
$$= 1 - exp\left\{-exp\left(-\frac{y_d^i - lnx_d' - z^i\theta_d' + \varepsilon_d^k}{\sigma_d}\right)\right\} \tag{5.9}$$

Furthermore, the survival function with respect to the real elapsed time t^i is defined as

$$S_w(\, y_d^i | x_d^i, z^i) \\ = 1 - exp\left\{-exp\left(-\frac{lnf_d(t^i) - lnx_d^i - z^i\theta_d' + \varepsilon_d^k}{\sigma_d}\right)\right\} \tag{5.10}$$

Thus, a survival function Eq. (5.10) can be derived for the continuous quantity deterioration hazard model.

5.3.2 Correlation Structure of Multi-dimensional Deterioration Events

The joint probability distribution of the heterogeneity parameters ε_d^k for $d(=1,\ldots,D)$ types of deterioration events in a certain category $k\ (=1,\ldots,K)$ is represented using a copula C. An overview of copulas is given below. For a detailed review of copulas, please refer to [7] – [9].

Let $P(\varepsilon_1,\ldots,\varepsilon_D)$ be the continuous joint distribution function of D random variables $\varepsilon_1,\ldots,\varepsilon_D$ with marginal distributions $P_1,\ldots,P_D$, then from Sklar's Theorem [10], there exists a copula C uniquely satisfying

$$P(\varepsilon_1,\ldots,\varepsilon_D) = C(P_1(\varepsilon_1)\ldots,P_D(\varepsilon_D)) \tag{5.11}$$

The $C(P_1(\varepsilon_1)\ldots,P_D(\varepsilon_D))$ generated by applying the marginal distributions $P_1(\varepsilon_1)\ldots,P_D(\varepsilon_D)$ to the copula C is a joint distribution function with the marginal distributions in the interval $[0,1]$.

In addition,

- For each $u_d = P_d\ (\varepsilon_d)\ \in\ [0,1]\ (d\ =\ 1,\ldots,D)$:

$$C(u_1,\ldots,u_{d-1},0,u_{d+1},\ldots,u_D) = 0 \tag{5.12}$$

- For each $u_d = P_d\ (\varepsilon_d)\ \in\ [0,1]\ (d\ =\ 1,\ldots,D)$:

$$C(1,\ldots,1,0,u_d,1,\ldots,1) = u_d \tag{5.13}$$

- For all $(u_1^1, \ldots, u_D^1), (u_1^2, \ldots, u_D^2 \in\ [0,1]^D\ satisfying\ u_d^1 \leq u_d^2$:

$$\sum_{i_1=1}^{2} \ldots \sum_{i_1=1}^{2} (-1)^{\sum_{s=1}^{D} i_s} C(u_1^{i_1}, \ldots, u_D^{i_D}) \geq 0 \tag{5.14}$$

A function C in which all the three properties described above are satisfied is defined as a copula. In this case, the joint probability density function $p(\varepsilon)$ of the heterogeneity parameter vector $\varepsilon_d = (\varepsilon_d^1, \ldots, \varepsilon_d^{\mathrm{K}})$ of individual deterioration events is the copula distribution function $C(P_1(\varepsilon_1) \ldots, P_D(\varepsilon_D))$ or probability density function $\mathrm{c}(\mathrm{P}_1(\varepsilon_1) \ldots, \mathrm{P}_\mathrm{D}(\varepsilon_\mathrm{D}))$ can be expressed as

$$\begin{aligned} p(\varepsilon) &= \frac{\partial^D C(P_1(\varepsilon_1) \ldots, P_D(\varepsilon_D))}{\partial(P_1(\varepsilon_1) \ldots, \partial P_D(\varepsilon_D))} \prod_{d=1}^{D} p_d(\varepsilon_d) \\ &= \mathrm{c}(\mathrm{P}_1(\varepsilon_1) \ldots, \mathrm{P}_\mathrm{D}(\varepsilon_\mathrm{D})) \prod_{d=1}^{D} p_d(\varepsilon_d) \end{aligned} \tag{5.15}$$

where $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_D)$ holds. The probability density function pd of the marginal distribution P_d follows a normal distribution

$$p_d(\varepsilon_d) = -\frac{1}{\sqrt{2\pi\phi_d^2))}} exp\left(-\frac{\varepsilon_d^2}{2\phi_d^2}\right) \tag{5.16}$$

Various copulas have been proposed to represent joint probability distributions using information about the marginal distribution. This study, employs the one-parameter Archimedian copula model [11]. The model structure has been widely used especially in financial fields due partly to its well-known random number generation method and subsequent practicality. The distribution function $C(u_1, \ldots, u_D)$ of the one-parameter Archimedian copula among D variables whose marginal distribution functions are $P_1(x_1) = u_1, \ldots, P_D(\varepsilon_D)) = u_D$ can be expressed using the generating function $\zeta\ (u_d)$ as

$$C(u_1, \ldots, u_D) = \zeta^{-1}\left(\sum_{d=1}^{D} \zeta\,(u_d)\right) \tag{5.17}$$

For the Archimedean copula, the following property holds

$$C(1, \ldots, 1, u_{d_1}, 1, \ldots, 1, u_{d_2}, 1, \ldots, 1) = \mathrm{C}\, u_{d_1}, u_{d_2}) \tag{5.18}$$

In this study, three types of Archimedean copulas were considered: the Gumbel copula [12], the Clayton copula [13], and the Frank copula [14]. Table 5.1 shows the generating function, distribution function, and probability density function for the Gumbel, Clayton and Frank copulas. The multivariate joint probability density functions of the Gumbel and Frank copulas are difficult to express in general form and are obtained by partial differentiation of the distribution functions as needed, depending on the number of variables.

In addition, the parameters of the Gumbel copula satisfy $\alpha \in (1, \infty)$ and those of the Clayton and Frank copulas satisfy $\alpha \in (0, \infty)$. In order to select an appropriate copula, [15] proposed a copula selection method based on the information criterion considering the selection among copulas with different number of parameters. In this study, the Widely Applicable Information Criteria (WAIC) [16], which has asymptotically the same expected value and variance as the generalization loss, was adopted as the information criterion for copula selection. The WAIC is suitable as an evaluation index for statistical models with complex structures including irregular models.

5.3.3 Observability of Deterioration Events and Connectivity Conditions

Deterioration state of a facility may be evaluated by different types of management indices for deterioration. However, it is not always possible to obtain data on the indices at the same inspection period. Furthermore, depending on facilities, it may not be possible to acquire inspection data on all deterioration events. Due to the partial observable nature of such

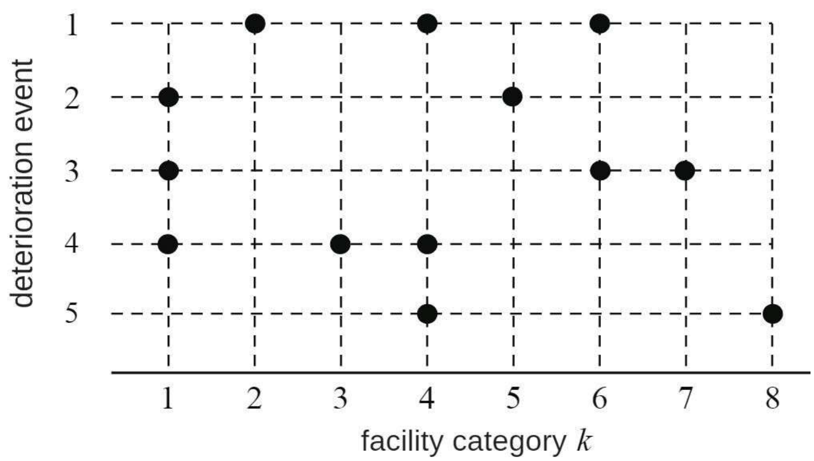

Figure 5.2.a Data acquisition pattern 1 of a certain facility category k.

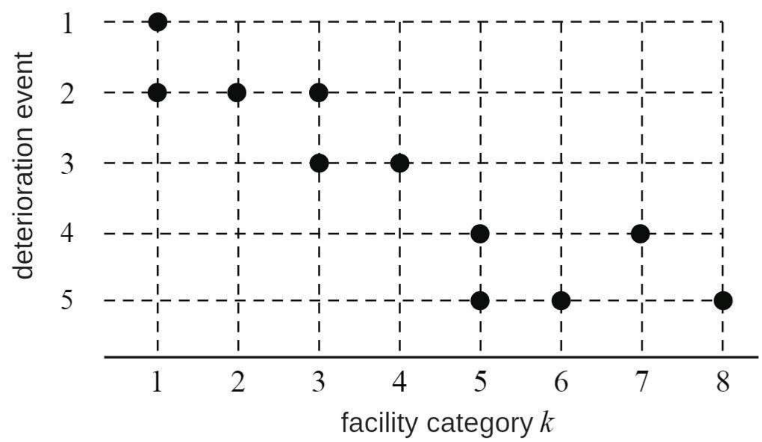

Figure 5.2.b Data acquisition pattern 2 of a certain facility category k

multidimensional deterioration events, it is impossible to evaluate multidimensional deterioration events using a single aggregated deterioration management index. It may however be considered that a correlation exists between the different indices derived from survey data. Therefore, in this study, the entire multidimensional deterioration process is estimated using partially observed information obtained from different deterioration processes.

In formulating the multi-dimensional model by estimating the unknown parameters of copulas, the concurrent observability of deterioration event data in relation to categories must be considered. For instance, consider 8 facility categories $k = 1,\ldots,8$ and 5 deterioration events $d = 1,\ldots,5$ as shown in Figure 5.2. A black circle in the figure signifies here a deterioration event index has been measured. In Figure 5.2.a, deterioration events 2, 3, and 4 are observed for the category 1, and events 1, 4, and 5 are observed for the category 4. In this example, by using the inspection data for the category 1 and 4, the correlation structure among all deterioration events $1,\ldots,5$ can be estimated using copulas. In this case, the deterioration events are said to satisfy the connectivity condition. In the Figure 5.2.b, there is no category in which the first three events (1, 2, and 3) and the last two events (4 and 5) are observed at the same time. In this case, the connectivity condition is not satisfied. Since copulas represent the distribution of the concurrent occurrences of heterogeneity parameters, it is desirable that the observed data satisfy the connectivity condition in order to minimize the estimation bias of copulas. In this research, the correlations among deterioration events for each category are expressed using copulas assuming that all events are connectable.

Let ω^k denote deterioration events observed for the category k ($k = 1,2,\ldots,K$). For instance, in Figure 5.2.a, deterioration events 2, 3, 4 are observed in category 1, and therefore $\omega^1 = \{2,3,4\}$. For the category 2, only event 1 can be observed, and the deterioration event group can be expressed as $\omega^2 = \{1\}$.. For arbitrary deterioration events d, d' ($d, \mathrm{d}' = 1,\ldots,D$), the dummy variable $\delta_{\mathrm{d,d'}}$ is defined as

$$\delta_{\mathrm{d,d'}} = \begin{cases} 1, & if\ k\ exists\ which\ satisfies\ d, \mathrm{d}' \in \omega^k \\ 0, & Otherwise \end{cases} \tag{5.19}$$

For a $D \times D$ matrix $\boldsymbol{H}$ whose dummy variable $\delta_{\mathrm{d,d'}}$ is a (d, d') element, the followingcondition must be satisfied.

$$x_D H = 1 \tag{5.20}$$

The symbol x_D denotes the Boolean operation of multiplying the matrix $\boldsymbol{H}$ by D times. The $\mathbf{1}$ is a $D \times D$-dimensional matrix with all elements being 1. The condition Eq. (5.20) is defined as the connectivity condition.

5.3.4 Partial Observation Results and Joint PDF

As elaborated above, for each category, correlations between deteriorating events are expressed using copulas. It is assumed that deterioration events can be linked to each other even if inspection data for all deteriorated events is not necessarily available for each category as illustrated in Figure 5.2.a. Based on the set of observable deterioration events for a category, the dummy variable δ_d^k representing the relationship between the category and each deterioration event is defined as

$$\delta_d^k = \begin{cases} 1, & for\ d \in \omega^k \\ 0, & for\ d \notin \omega^k \end{cases} \tag{5.21}$$

The heterogeneity parameter vector corresponding to observable deterioration events in category k is expressed as $\hat{\varepsilon}^k = \{ P_1\,(\varepsilon_1^k)^{\delta_1^k}, \ldots, P_D\,(\varepsilon_D^k)^{\delta_D^k} \}$. In this case $\delta_d^k = 0$, $P_d\,(\varepsilon_d^k)^{\delta_d^k}$=1 should be satisfied. The copula distribution function $\bar{C}(\hat{P}^k(\hat{\varepsilon}^k))$ expressing correlations between marginal distributions of partial heterogeneity parameter vector $\hat{\varepsilon}^k$ is

$$\bar{C}(\hat{P}^k(\hat{\varepsilon}^k)) = C(P_1\,(\varepsilon_1^k)^{\delta_1^k}, \ldots, P_D\,(\varepsilon_D^k)^{\delta_D^k}) \tag{5.22}$$

From the one-parameter Archimedean copula property, Eq. (5. 18), Eq. (22) represents the copula's marginal distribution function for the heterogeneity parameter focusing only on deterioration events in the set ω^k. Let R^k deterioration events belonging to the set ω^k of observable events in the category k be denoted by $\hat{d}_{r^k}^k(r^k = 1, \ldots, R^k)$ respectively. The copula probability density function $\bar{c}(\hat{P}^k(\hat{\varepsilon}^k))$ for each category k is

$$\bar{c}\left(\hat{P}^k(\hat{\varepsilon}^k)\right) = \frac{\partial^{R^k}\bar{C}\left(\hat{P}^k(\hat{\varepsilon}^k)\right)}{\partial\hat{P}_{\hat{d}_1^k}\left(\varepsilon_{\hat{d}_1^k}\right)\ldots\partial\hat{P}_{\hat{d}_{R^k}^k}\left(\varepsilon_{\hat{d}_{R^k}^k}\right)} \tag{5.23}$$

The joint probability density function $\hat{p}^k(\hat{\varepsilon}^k)$ of the heterogeneity parameter vector $\hat{\varepsilon}^k$ for the category k can be expressed, using the copula's probability density function $\bar{c}(\hat{P}^k(\hat{\varepsilon}^k))$, marginal probability density function $p_d(\varepsilon_d^k)$, and dummy variable δ_d^k, as

$$\hat{p}^k(\hat{\varepsilon}^k) = \bar{c}(\hat{P}^k(\hat{\varepsilon}^k)).\prod_{d=1}^{D}\{p_d(\varepsilon_d^k)\}^{\delta_d^k} \tag{5.24}$$

Using the joint probability density function Eq. (5.24), even if there is no observed data for a certain deterioration event d' in a certain category k, given that the inspection data for the remaining deterioration events d is acquired, the marginal distribution of the heterogeneity parameter can be estimated.

5.3.5 Likelihood Function

Consider that several deterioration management indices for each deterioration event are available for a structure i^k $(i^k = 1,\ldots,1^k)$ in category k. The inspection data for deterioration event d of structure i^k belonging to category k is defined as $\xi_d^{i^k} = (\bar{x}_d^{i^k},\ \bar{t}_d^{i^k}, \bar{z}_d^{i^k})$, and the total visual and the total visual inspection data collected in $\bar{\boldsymbol{\Xi}}$. The symbol "$\overline{\ \ }$" denotes measured values. Let $\xi^{i^k} = \{\ \xi_d^{i^k}: d \in \omega^k\}$ specify that the data satisfies the connectivity condition. The likelihood of observing the inspection data can be expressed with the conditional probability density function of the structure's real life and the joint probability density function of the heterogeneity parameters as

$$L(\lambda|\xi^{i^k}) = \bar{c}(\hat{P}^k(\hat{\varepsilon}^k)).\prod_{d=1}^{D}\prod_{k=1}^{K}\prod_{i^k=1}^{1^k}\tau(\xi^{i^k}|\beta_d,\theta_\mathrm{d},\varepsilon_d^k,\ \sigma_\mathrm{d})p_d(\varepsilon_d^k)\}^{\delta_d^k} \tag{5.25}$$

Where $where\ \lambda = (\beta,\theta,\varepsilon,\sigma,\phi,\alpha)$ is the parameter vector and

$$\tau\left(\xi^{i^k}|\beta_d,\theta_d,\varepsilon_d^k,\ \sigma_d\right)\frac{\dot{f}_d\bar{t}^i}{\sigma_d\ f_d\left(\bar{t}^i\right)}.exp\left\{-exp\left(-\frac{ln\,f_d\left(\bar{t}^i\right)-ln\bar{x}_d^i\ -\ \bar{z}^i\theta_d'}{\sigma_d}\right.\right. - \left.\frac{ln\,f_d\left(\bar{t}^i\right)-ln\bar{x}_d^i\ -\ \bar{z}^i\theta_d'\ +\ \varepsilon_d^k}{\sigma_d}\right\} \tag{5.26}$$

The likelihood $L(\lambda|\bar{\Xi})$ of observing the data set $\bar{\Xi}$ is

$$L(\lambda|\bar{\Xi}) = \prod_{d=1}^{D}\prod_{k=1}^{K}\left[\bar{c}(\hat{P}^k(\hat{\varepsilon}^k)).\prod_{d=1}^{D}\prod_{k=1}^{K}\prod_{i^k=1}^{1^k}\left\{\tau(\xi^{i^k}|\beta_d,\theta_\mathrm{d},\varepsilon_d^k,\ \sigma_\mathrm{d})p_d(\varepsilon_d^k)\right\}^{\delta_d^k}\right] \tag{5.27}$$

The parameters in the defined likelihood function can be estimated using an iterative procedure such as the Markov Chain Monte Carlo (MCMC) method using the Metropolis Hastings (MH) algorithm.

5.4 Empirical Analysis

5.4.1 Data Summary

In the empirical application, the developed multidimensional deterioration process model using continuous quantities was applied to intercity highway pavements in Japan. The road surface condition (cracking rate, rutting area, IRI) and load-bearing capacity data (D_{ind}) obtained from the road surface condition and FWD surveys conducted from 2006 to 2021 were used. The dataset contains information on each location on the highway pavement, including (1) locational information such as route name, lane classification, and kilometer post, (2) records of repair, i.e, when the repairs were carried out and up to which layers the repairs were

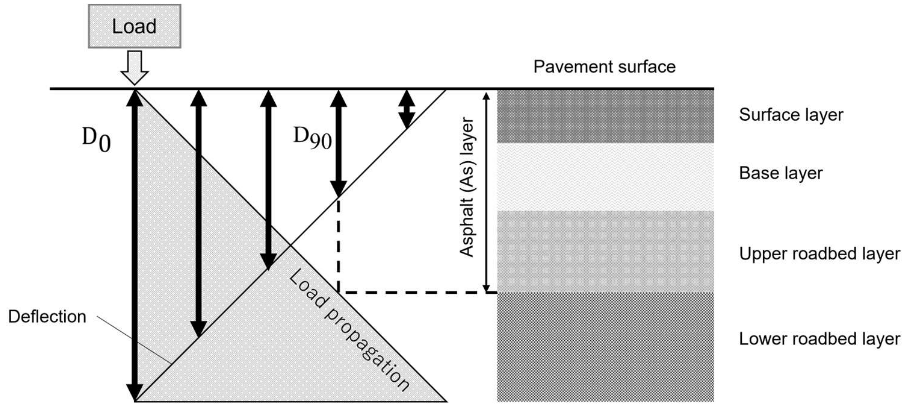

Figure 5.3 Pavement structure and FWD measurements

undertaken, and (3) pavement composition such as surface layer, base layer, upper roadbed, and lower roadbed type and thickness.

Pavement's index for load bearing capacity is defined as

$$D_{ind} = \frac{D_0 - D_{90}}{A} * 10^6 \tag{5.28}$$

D_{ind} is an index for evaluating pavement load-bearing capacity based on the estimated deflection in the asphalt layer (hereinafter called As layer), where D_0 is the deflection in mm at the loading point, D_{90} is the deflection in mm at a distance of 90 cm from the loading point, and A is the design thickness in mm of the As layer. The relation among the pavement structure and FWD measurements is illustrated in Figure 5.3. D_0 refers to the deflection due to load propagated throughout the entire pavement structure. D_{90} is horizontally 90 cm away from the loading point and shows the deflection from the load propagated through the lower roadbed layer. The rationale behind (28) is that $D_0 - D_{90}$ determines the deflection from the load throughout the layer. An original form of (5.28) was proposed by [17] which was further modified by the authors to account for the effect of layer thickness. The estimated D_{ind} was also used as a measure of the subsurface strength of pavements in the empirical study.

Pavement deterioration is a complex process consisting of road surface and loadbearing capacity deterioration, and prior research has attempted to examine their relation (e.g., [18] - [19]). It is considered that a correlation exists between the road surface and load-bearing capacity deterioration indices. The uncertainty of this correlation was expressed using copulas. In addition, since the FWD survey is a method to diagnose the pavement load-bearing capacity by dropping a weight on the pavement surface and measuring the amount of deflection caused by the weight, it is difficult to obtain load-bearing capacity indices over a wide area and at a high frequency because it may necessitate road traffic restriction which is undesirable for road users.

On the other hand, the road surface condition surveys conducted using a moving vehicle do not require traffic restrictions. Thus, even when inspection results are only partially observed in some inspections (deterioration events), the multidimensional deterioration process model can be used to estimate the entire multidimensional deterioration process using consolidated data from multiple deterioration events and structure categories.

The total number of structure categories in the data was 3,565 with each pavement section being 10 m long, the minimum unit of the road surface index evaluation length. Of these categories, 312 categories contained both road surface and load-bearing capacity data, thus satisfying the connectivity condition.

5.4.2 Estimated Results

For the estimation of parameters, data samples of drainage pavements, which is a standard type of the surface layer throughout Japan's intercity highway pavement, are used for analysis to avoid potential biases from incorporating different types of surface layer. For the pavement load-bearing capacity, D_{ind} was used, whereas for the road surface condition, three indices were used; i.e., the cracking rate, rutting depth, and IRI. In order to independently evaluate the relationship between the load-

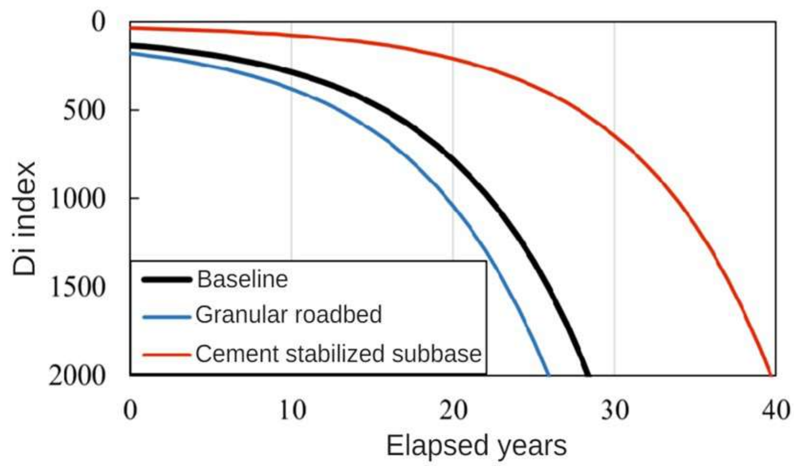

Figure 5.4 Performance curve based on D_{ind}

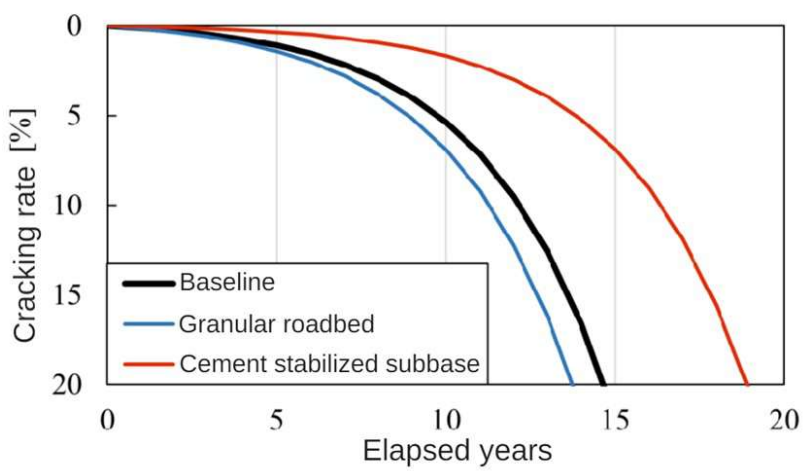

Figure 5.5 Performance curve based on cracking

bearing capacity index and each road surface index, a multidimensional deterioration process model using individual continuous quantities was applied to analyze a total of three combinations: (1) $D_{ind} - cracking\ rate$, (2) $D_{ind} - rutting\ depth$, and (3) $D_{ind} - IRI$. The characteristic variable groups were defined as granular roadbed and cement stabilized roadbed. The characteristic variable was specified using the following dummy variable.

$$z_i = \begin{cases} 0, & when\ point\ i\ is\ a\ granular\ roadbed \\ 1, & when\ point\ i\ is\ a\ cement\ stabiliszed\ roadbed \end{cases} \tag{5.29}$$

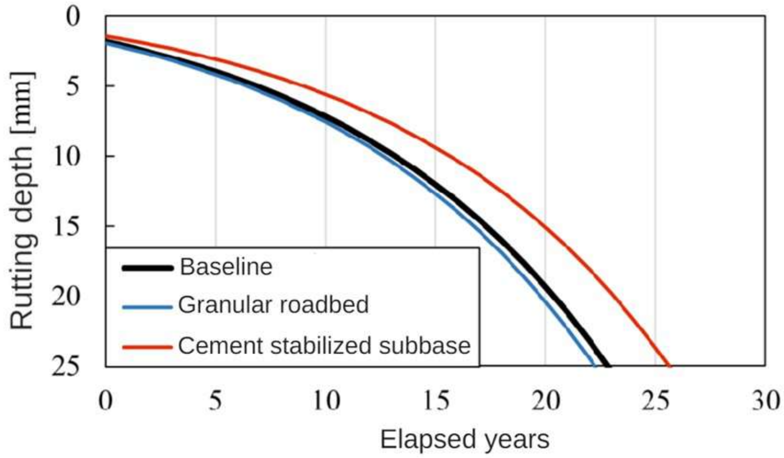

Figure 5.6 Performance curve based on rutting

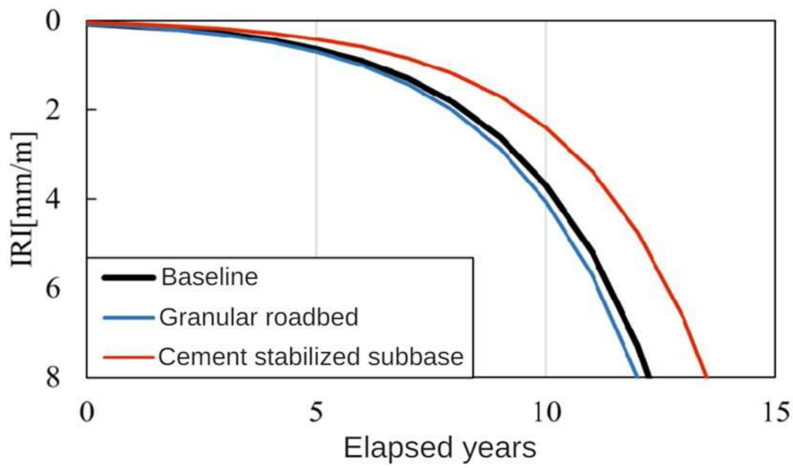

Figure 5.7 Performance curve based on IRI

By estimating the parameter $\boldsymbol{\theta}$ based on the characteristic variable z_i, the effect of using granular or cement stabilized roadbeds as the subgrade can be evaluated.

Table 5.3 shows the estimated parameters of the load-bearing capacity indices $\beta^{D_{ind}}$, $\theta^{D_{ind}}, \sigma^{D_{ind}}$, the 95% confidence intervals of the Bayesian estimation, and the Geweke statistics. Similarly, Table 5.4 shows results for road indices (cracking: β^{crack}, $\theta^{crack}, \sigma^{crack}, \alpha^{crack}$, *rutting* : β^{rut}, $\theta^{rut}, \sigma^{rut}, \alpha^{rut}$, IRI: β^{IRI}, $\theta^{IRI}, \sigma^{IRI}, \alpha^{IRI}$). For cracking, only β_1^{crack} and β_2^{crack} are shown assuming $\beta_3^{crack} = 0$ for a newly constructed or repaired pavement. The parameters showed high convergence with the Geweke diagnostics falling within the [-1.96, 1.96] limits with 0 specifying perfect convergence. These parameters can be used to generate illustrative performance curves shown in Figure 4 - 7. The results showed that cement stabilized pavements have longer life compared to granular roadbed pavements for all performance curves as cement stabilization increases subbase strength.

Table 5.2 Copula candidates and WAIC

Copula	D_{ind} – Cracking rate	D_{ind} – Rutting	D_{ind} – IRI
Gumbel	18,651	16,751	15,993
Clayton	18,568	16,777	16,013
Frank	18,608	16,787	16,004

Table 5.3 Estimated parameters for load bearing capacity $\boldsymbol{\beta}$, $\boldsymbol{\theta}$, σ

Parameter	Mean	Upper 5%	Lower 5%	Geweke statistics
$\beta_1^{D_{ind}}$	74.81	96.58	44.57	-0.156
$\beta_2^{D_{ind}}$	1.126	1.137	1.109	0.086
$\beta_3^{D_{ind}}$	151.5	162.5	142.2	0.677
$\theta^{D_{ind}}$	1.602	2.271	0.353	1.697
$\sigma^{D_{ind}}$	1.322	1.422	1.171	-0.257

The WAIC of the entire model including copulas is shown in Table 5.2. Three types of copulas were used: Gumbel, Clayton, and Frank copulas. From the same table, the Clayton copula was selected as the best copula for the $D_{ind} - cracking\ rate$, and the Gumbel copula for the $D_{ind} - rutting$ and $D_{ind} - IRI$ as they achieved minimum WAIC scores. The flexible function $f_d\ (t, \beta)$ (polynomial function, power function, exponential function) representing the baseline model for each indicator was also evaluated using WAIC, from which the exponential function $f_d\ (t, \beta) = \beta_1(\beta_2^t - 1) + \beta_3$ was employed for each pair of indicators.

Table 5.4 Estimated parameters for road surface indices $\boldsymbol{\beta}$, $\boldsymbol{\theta}$, σ

	Parameter	Mean	Upper 5%	Lower 5%	Geweke statistics
Cracking	β_1^{crack}	0.395	0.405	0.375	0.071
	β_2^{crack}	1.311	1.315	1.304	0.838
	θ^{crack}	1.410	1.443	1.356	0.883
	σ^{crack}	1.120	1.129	1.103	-1.491
	α^{crack}	0.866	1.330	0.210	0.273
Rutting	β_1^{rut}	5.007	5.154	4.784	-1.629
	β_2^{rut}	1.086	1.087	1.083	1.531
	β_3^{rut}	2.164	2.191	2.117	0.655
	θ^{rut}	0.302	0.312	0.284	0.924
	σ^{rut}	0.451	0.457	0.438	-0.981
	α^{rut}	1.085	1.182	1.002	0.938
Rutting	β_1^{IRI}	0.771	0.793	0.727	0.816
	β_2^{IRI}	1.143	1.145	1.139	-0.548
	β_3^{IRI}	0.441	0.047	0.034	-0.143
	θ^{IRI}	0.270	0.286	0.243	0.403
	σ^{IRI}	0.606	0.613	0.593	-1.439
	α^{IRI}	1.084	1.178	1.003	-1.571

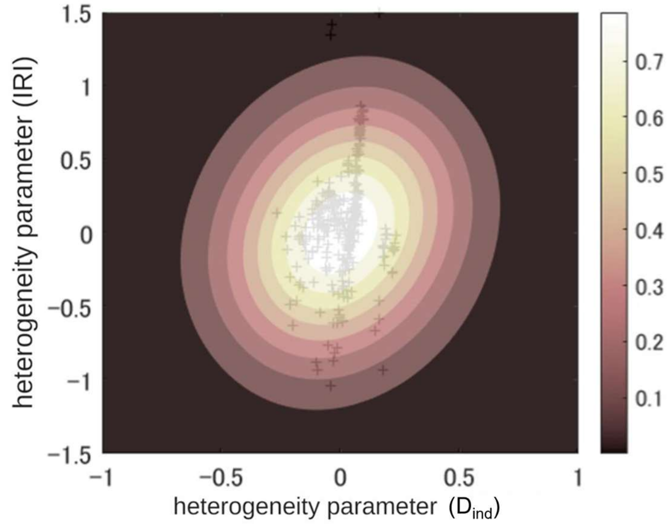

Figure 5.10 Joint probability density for (εD_{ind} , ε_{IRI}).

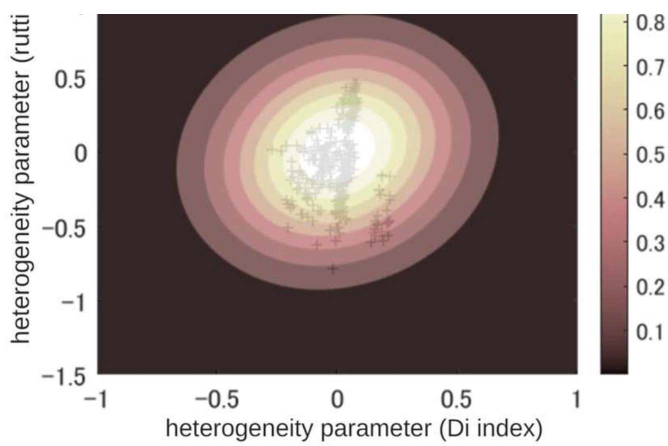

Figure 5.9 Joint probability density for (ε_{Dind} , ε_{rut}).

5.4.3 Joint PDF for Heterogeneity Parameters

In the multidimensional deterioration process model with continuous quantities, the copula probability density function and the marginal probability density function can be used to represent the joint probability density functions of the heterogeneity parameters for multiple deterioration events. The joint probability density functions of the heterogeneity parameters of the $D_{ind} - crack\ rate$, $D_{ind} - rutting$ and $D_{ind} - IRI$ are shown in Figure 8, 9 and 10. From the joint probability plots, although the variation of the heterogeneity parameter of the $D_{ind} - crack\ rate$ of Figure 5.8 was the largest among the three road surface indices, its correlation coefficient with the heterogeneity parameter of the D_{ind} was 0.597, confirming a positive correlation between pavement surface cracking and subsurface deterioration. The $D_{ind} - rutting$ in Figure 5.9 had the smallest correlation coefficient at 0.160, with both heterogeneity parameters concentrated around 0. The $D_{ind} - IRI$ of Figure 5.10 also showed the same trend as the $D_{ind} - rutting$, but the variability of the IRI heterogeneity parameter was relatively larger, with a correlation coefficient of 0.219.

The joint probability density functions of the heterogeneity parameters presented above showed that in this empirical study, the D_{ind}-crack rate combination has interactive effects for both deterioration processes (surface and subsurface). In the D_{ind}-crack rate combination, the joint probability density function has a distorted shape in the third quadrant because the Clayton copula with the lowest WAIC score was used for estimation.For the Clayton copula, the degree of dependence among random variables is the multidimensional deterioration process model with continuous quantities, the copula probability density function and the marginal probability density function can be used to represent the joint probability density functions of the heterogeneity parameters for multiple deterioration events relatively strong in the lower left and weak in the upper right of the plot. This means that the correlation is particularly strong in the third quadrant, where both heterogeneities take small values, and that when either the D_{ind} or the crack rate takes small values.

Three types of Archimedian copulas; i.e., the Gumbel, Clayton, and Frank copulas were used in the estimation of the correlation between the surface and subsurface deterioration events. However, it is desirable to estimate using a variety of copulas as candidates so as to select models that further reduce the WAIC.

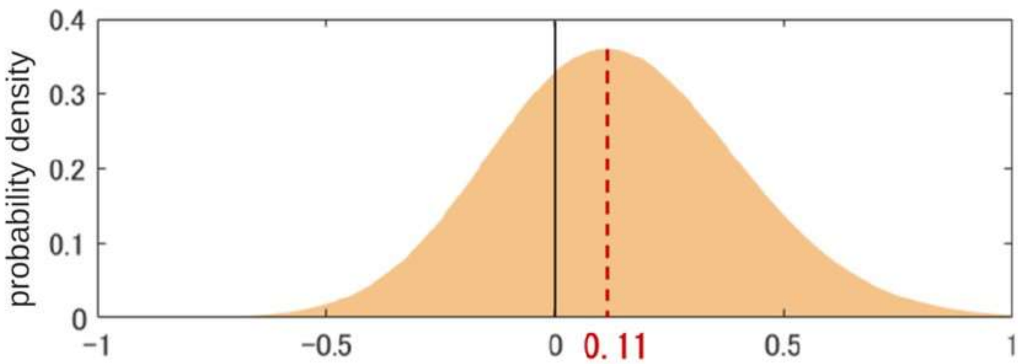

Figure 5.11 Probability density function for εD_{ind} (when $\varepsilon_{\text{crack}} = 1$).

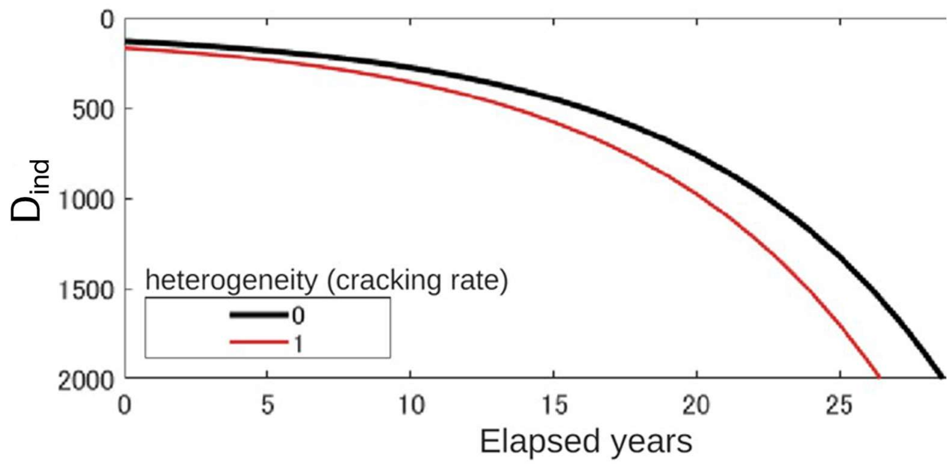

Figure 5.12 Variation of load bearing capacity index due to differences in road surface index.

5.4.4 Multidimensional Deterioration Process

As discussed in detail earlier, the FWD test used to estimate pavement load-bearing capacity requires traffic restrictions, whereas road road surface condition surveys do not. Hence, cases where the load-bearing capacity index is unknown and the road surface index is known (measured multiple times) are prevalent in the data set. Therefore, the unknown load-bearing capacity index can be quantitatively predicted using the joint probability density functions of the load-bearing capacity index and the heterogeneity of each road surface index. In this application case, a positive correlation was observed between the cracking rate and the load bearing capacity index, and there was a weak correlation for the combination of the load bearing capacity index - rutting area and the load bearing capacity index - IRI, so a joint probability density function for the heterogeneity parameters (εD_{ind}, ε_{crack}) shown in Figure 5.8 was used to predict the unknown load bearing capacity index.

If the heterogeneity $\varepsilon_{crack} = 1$ of the crack rate at a point i is known, then through application of the joint probability density function, the probability density distribution of the heterogeneity εD_{ind} of the load bearing capacity index as shown in Figure 5.11 can be estimated. The expected value of εD_{ind} was 0.11, suggesting that the deterioration rate was comparatively larger. It is also possible to use the probability density function to assess hazard risk where heterogeneity is greater than the expected value. The expected deterioration performance curves of the load-bearing capacity index are shown in Figure5.12 assuming only crack rate and $\varepsilon_{crack} = 0$ and $\varepsilon_{crack} = 1$ predicted using the results in Figure 5.11. From the same figure, it is possible to quantitatively evaluate load-bearing capacity deterioration rates when the crack rate heterogeneity is higher.

5.4.5 Practical Implications

In this research, the correlation among heterogeneity parameters in a continuous quantity deterioration hazard model that takes heterogeneity into account was quantified using copulas. Through the evaluation of the deterioration rate of infrastructural facilities from multiple perspectives, the following pavement intervention considerations can be made. Focusing on Figure 5.8, the group located in the first quadrant, where the heterogeneity parameter is greater than 0 for both the road surface and load bearing capacity indices, shows faster deterioration progress for both the road surface and load bearing capacity. For this group, intensive interventions should be performed, taking into account the need for not only repairs of the shallow layers such as the surface and base layers, but also large-scale maintenance and renewal involving deeper layers including the upper and lower roadbeds. Next, for groups in the fourth quadrant, where the heterogeneity parameter of the road surface index is greater than 0 and the heterogeneity parameter of the load-bearing capacity index is less than 0, replacement of the surface and base layers should be carried out as pavement damage is likely confined only to shallow layers. For groups in the second quadrant, where the heterogeneity parameter of the road surface index is less than 0 and the heterogeneity parameter of the load-bearing capacity index is greater than 0, there is a possibility that deterioration is developing in the deeper pavement layers and therefore intensive intervention should be conducted and a rehabilitation plan that takes into account large-scale rehabilitation and renewal when damage appears on the road surface be established. No intervention may be required in the quadrant with both heterogeneity parameters less than 0, however, regular inspection can be encouraged. Furthermore, the joint probability that a group is located in each quadrant of Figure 5.8 can be calculated as 0.33 for the first quadrant, 0.17 for the second quadrant, 0.33 for the third quadrant and 0.17 for the fourth quadrant using the joint probability density function for the heterogeneity parameters. These probabilities represent the proportion of the total road sections under observation located in each quadrant, and may provide useful information for budget planning and major repair projects.

Additionally, when only road surface indices are obtained, it is possible to quantitatively evaluate whether the group in question is located in the first or second quadrant, or the third or fourth quadrant, using fragmentary information in the form of heterogeneity parameters of the load bearing capacity index. The ability to represent multidimensional deterioration processes probabilistically from partial observation information is an important feature of this research with practical applications in the case of incomplete infrastructure monitoring data.

5.5 Conclusion

In this study, a multidimensional deterioration process model using continuous quantities was applied to pavement load-bearing capacity and road surface indices (crack rate, rutting depth, and IRI) estimated through FWD tests and road surface condition surveys, respectively. An empirical analysis was conducted to contribute to the planning of preventive maintenance and major rehabilitation. Specifically, the progression process of individual deterioration events was expressed using a continuous quantity deterioration hazard model that takes heterogeneity into account, and the heterogeneity between the expected life at the management standard value and the deterioration rate specific to each subject facility was estimated. The heterogeneity of pavement load-bearing capacity and road surface indices was obtained using a multidimensional deterioration process model and the correlation structure among deterioration events expressed using an Archimedian copula. This representation enabled the evaluation of the need for large-scale intervention or preventive repair based on the quadrant in which a given pavement section was grouped. Furthermore, when the methodology proposed in this study was applied to actual highway inspection data, a positive correlation was observed between the crack rate and load-bearing capacity index and the correlation was particularly strong in areas where the heterogeneity between the two was small.

As a part of future research, the following two issues need to be addressed. First, applicability of the proposed method must be verified by increasing the number of application cases. The sections analyzed in this application case study are those with particularly advanced deterioration among the highways under a certain jurisdiction of intercity highway managing company, and generalizability of the results is yet to be examined. Therefore, the finding that among the three road surface indices, only cracking rate was strongly correlated with the load-bearing capacity index is valid only for the sections selected for this study application. In the future, it is necessary to apply the proposed method to several sections to clarify the interconnectedness of the road surface indices and the load-bearing capacity index. Second, the different correlations among several deterioration indices need to be expressed in more detail. In this study, one-parameter Archimedian copulas were used for each combination of load-bearing capacity and a road surface index, but it may be preferable to use two-parameter Archimedian copulas, which allow for more flexible expressions of dependence structures. It is also possible to analyze the correlation structure of three or more indicators simultaneously. The correlations between deterioration events can be described more precisely by using the vine copula [20], which defines different types of copulas between each index.

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Chapter 6：Conclusions

6.1 Brief Summary

This dissertation focused on the study of deterioration of road assets in Nepal by applying hazard-based deterioration models to improve the road maintenance decision-making process. Considers the Nepal's traffic condition, monsoon dominated climatic condition, and limited budget for road maintenance, this study focused on developing practical and predictive models for road agencies to help manage road assets more effectively and sustainably.

The research began by assessing the limitations of the current Road Asset Management (RAM) system in Nepal, particularly its reactive maintenance approach, lack of predictive models, and underutilization of environmental and traffic-related data. To address these gaps, stochastic models were developed, primarily focusing on the Markov hazard process and life expectancy modeling based on surface condition indicators such as the Surface Distress Index (SDI) and International Roughness Index (IRI). In addition, the research incorporated traffic and monsoon rainfall as a critical environmental factor for pavement deterioration. Advanced spatial interpolation techniques (IDW and EBK3D) were used to estimate monsoon rainfall, allowing the integration of site-specific environmental data into the deterioration models.

A component of the dissertation involved the development of a multidimensional continuous deterioration model using copula-based statistical frameworks. This study uses surface and subsurface pavement inspection data from highways in Japan, where more comprehensive performance monitoring systems, including Falling Weight Deflectometer (FWD) testing, are already in operation. The study also proposed a continuous deterioration framework that models the correlation among different performance indicators, offering more accurate and realistic surface and subsurface pavement deterioration projections.

The methodological framework of this model can be applied to the Nepal highway, where the FWD survey has been newly introduced and is currently limited to selected highway sections. Therefore, the copula-based deterioration model developed in this chapter can be assessed using the pavement inspection data sets from Nepal in the future to predict load-bearing capacity deterioration using surface conditions, maintenance planning, and budget prioritization.

The empirical validation confirmed the models' applicability under Nepalese road and climatic conditions. The developed framework allows road agencies to forecast road asset deterioration, plan maintenance activities more effectively, and adopt a data-driven approach—providing a robust tool to improve the efficiency and long-term sustainability of road maintenance in Nepal.

6.2 Conclusions

This dissertation developed and validated hazard-based pavement deterioration models tailored to Nepal's unique geographic, climatic, and institutional contexts. The research incorporated environmental hazards, particularly monsoon rainfall, into deterioration predictions using advanced interpolation and hazard modeling techniques. This research demonstrates the relevance of a multidimensional pavement deterioration process using continuous quantities, considering the interaction between the pavement surface and the load-bearing capacity deterioration.

Key conclusions include:

1. When integrated with traffic and environmental data, the Markov hazard models provide a reliable tool for estimating pavement life expectancy and deterioration.
2. Incorporating rainfall hazard data significantly improves deterioration prediction accuracy, especially in monsoon-affected regions.
3. The copula-based continuous deterioration framework enhances the capacity to model complex interactions between multiple deterioration indicators.

Notably, the practical application of these models revealed that cost-effective strategies such as Combined Maintenance (CM) and upgrading high traffic low cost pavements with higher deterioration rate to superior asphalt concrete pavements are both technically viable and economically beneficial. This directly impacts road maintenance policies and practices in Nepal, helping agencies adopt proactive and long-term planning mechanisms.

6.3 Future Research

This study proposed a hazard-integrated framework for modeling pavement deterioration in Nepal's Strategic Road Network (SRN); however, several areas remain open for further research to enhance the model's robustness, adaptability, and practical value.

1. Expansion to Local Roads and Bridges: This research is limited to Strategic Road Network under DOR, there are other road agencies which manages significant portion of Local Road Networks (LRNs) in Nepal. Future research should extend the suitability of developed framework to cover LRNs and bridge infrastructure. This would support the development of a fully integrated RAMS.
2. Inclusion of Additional Environmental Variables: Future studies should incorporate various environmental and climatic variables such as temperature, humidity, and freeze-thaw cycles. These factors significantly affect pavement performance, and their integration would enable a more comprehensive understanding of environmental impacts on deterioration patterns, particularly in high-altitude and temperature-variable regions.
3. Differentiation by Pavement Type and Topography: The current model is general; future research can expand it to accommodate different pavement types, such as rigid and composite pavements, and apply it across diverse geographic regions of Nepal, including the plains, hills, and mountainous zones. This would help evaluate region-specific deterioration behaviors and support the formulation of localized maintenance strategies.
4. Enhanced Traffic Characterization: Due to data limitations, Average Annual Daily Traffic (AADT) was used as the primary traffic-related variable in this study. However, future models could include commercial traffic volume, particularly in Equivalent Single Axle Loads (ESAL), which provides a more accurate representation of pavement loading and stress conditions. This enhancement requires a more detailed traffic dataset with axle-load classifications.

5. Application of Mixed Markov Hazard Models for Heterogeneous Infrastructure: The current model estimates average deterioration across the network. Future research can employ mixed Markov deterioration hazard models to capture the heterogeneity of different infrastructure groups by incorporating categorical variables (e.g., terrain, material type, construction quality). This would allow group-specific modeling and improve forecasting precision.

By addressing these aspects, future studies can expand the developed framework's applicability, improve its forecasting capability, and contribute to a more resilient and economically efficient road asset management system in Nepal and other resource-constrained settings.