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A MARKOV CHAINS FOR STOCHASTIC MODELLING OF LAND USE CHANGE: A FRAMEWORK FOR ECONOMIC AND AGRICULTURAL POLICYMAKERS

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ABSTRACT:
The dynamic patterns of land use and land cover play a crucial role in shaping the agricultural, economic, and social landscapes of a region. In Karnataka, a rapidly developing state in India, changes in land use have become increasingly significant due to expanding urbanization, agricultural intensification, deforestation, and infrastructural growth. This study employs Markov Chain Analysis (MCA), a robust stochastic modelling technique, to analyze and predict land use transitions in Karnataka over 40 years. The ability of Markov Chains to estimate transition probabilities from one land use category to another makes it an ideal tool for understanding temporal trends and anticipating future land cover changes.
The primary aim of this study is to model and quantify the dynamics of land use change in Karnataka using Markov Chain Analysis. The objectives include: (1) identifying the major transitions among land use categories over time; (2) computing transition probability matrices to quantify the likelihood of shifts between these categories; and (3) projecting future land use scenarios based on historical trends to inform sustainable land management strategies.
The study's impact spans academia, industry, and policy. For sectors like agriculture, real estate, and infrastructure, it provides actionable insights into land availability and development trends. Policymakers can use the findings to guide zoning, conservation efforts, and long-term planning, ensuring a balanced approach to development and environmental protection. Overall, the research serves as a strategic tool for sustainable regional planning in Karnataka.

KEYWORDS: Land Use Pattern, Markov Chain Model, Stochastic Process, Transition Probability Matrix, Transition Area Matrix

LITERATURE REVIEW: The Markov Chain Model (MCM) is a stochastic process that predicts land use changes based on the transition probabilities of different land classes over time. As described by *Pontius and Malanson (2005)*, the Markov process assumes that future states of land use depend only on the current state, making it a memory-less model. This characteristic simplifies prediction modelling while still providing reasonably accurate short- to medium-term forecasts.

Several studies in Karnataka have applied the MCM to assess temporal land use transitions. For instance, *Ramachandra et al. (2012)* used Landsat satellite imagery for analyzing land cover changes in the Western Ghats region of Karnataka. By applying Markov Chain Analysis, the study was able to predict probable land cover scenarios and highlighted the degradation of forest cover due to anthropogenic pressures.

Similarly, *Manjunatha et al. (2015)* examined the Bangalore Urban and Rural districts and identified urban sprawl as a dominant transition, facilitated by policy shifts and economic growth. Their research demonstrated that MCM, when integrated with cellular automata (CA-Markov), enhances spatial precision in predicting urban expansion.

Another significant application of MCM in Karnataka is in agricultural land use studies. *Gowda and Ramesh (2017)* analysed cropping pattern changes in the Krishna River basin using multi-temporal satellite imagery and transition matrices derived from the Markov Chain. Their study provided insights into the effects of irrigation projects on cropping intensity and agricultural land conversion.

In the context of Karnataka, the state's diverse ecological zones—from the arid plains of North Karnataka to the ecologically sensitive Western Ghats—pose challenges for uniform land use modelling. Researchers like *Bharath et al. (2018)* emphasize region-specific calibration of models for improved reliability. They highlight that accurate land use prediction supports better urban planning, disaster risk reduction, and biodiversity conservation.

In conclusion, this paper serves as a robust statistical approach for modelling land use dynamics in Karnataka using transition probabilities by Markov Chain Analysis and forecasting the future land use pattern. As the state continues to witness rapid development and ecological pressures, using this model as predictive tools into planning and economic framework can significantly enhance sustainable land management practices in Karnataka.

METHODOLOGY: The secondary data for this article are collected from the Government of India's Ministry of Agriculture & Farmers Welfare Department of Agriculture & Farmers Welfare, Economics, Statistics and Evaluation Division, New Delhi. The study takes into account of 40 years data for analysis and uses Markov Chain Analysis, a robust stochastic modelling technique, to analyze and predict land use transitions in Karnataka from 1984 to 2022.

NINE-FOLD CLASSIFICATION LAND USE IN KARNATAKA

1. **Forest Area (F):** This includes all land classified either as forest under any legal enactment, or administered as forest, whether State-owned or private, and whether wooded or maintained as potential forest land.
2. **Area under Non-agricultural Uses (NA):** This includes all land occupied by buildings, roads and railways or under water, e.g. rivers and canals, and other land put to uses other than agriculture.
3. **Barren and Un-culturable Land (B):** This includes all land covered by mountains, deserts, etc. Land, which cannot be brought under cultivation except at an exorbitant cost is classified as unculturable whether such land is in isolated blocks or within cultivated holdings.
4. **Permanent Pasture and other Grazing Land (PP):** This includes all grazing land whether it is permanent pasture/meadows or not.
5. **Land under Miscellaneous Tree Crops, and Grooves etc. (T&G):** This includes all cultivable land, which is not included in 'Net Sown Area ' but is put to some agricultural use. Land under casuarina trees, thatching grasses, bamboo bushes and other groves for fuel, etc. which are not included under 'Orchards' are classified under this category.
6. **Culturable Waste Land (CW):** This includes land available for cultivation, whether taken up or not taken up for cultivation once, but not cultivated during the last five years or more in succession including the current year for some reason or the other.
7. **Fallow Lands other than Current Fallows (OF):** This includes all land, which was taken up for cultivation but is temporarily out of cultivation for a period of not less than one year and not more than five years.
8. **Current Fallows (CF):** It is cropped area, which is kept fallow during the current year.

9. Net Sown Area (NSA): This represents the total area sown with crops and orchards. Area sown more than once in the same year is counted only once

ANALYSIS: Land use pattern during the last 40 years 1984-2022.

Table 1 NINE-FOLD CLASSIFICATION OF LAND USE IN KARNATAKA (in 000' Hectares)

Sl. No.	Year	F	NA	B	CW	PP	T&G	CF	OF	NSA
		1	2	3	4	5	6	7	8	9
1	1983-84	3030	1143	816	485	1246	337	919	459	10605
2	1984-85	3047	1149	814	470	1193	339	1044	445	10549
3	1985-86	3057	1158	803	469	1164	342	1418	466	10172
4	1986-87	3061	1162	801	461	1156	351	1108	417	10533
5	1987-88	3061	1174	801	458	1135	326	942	417	10736
6	1988-89	3071	1182	800	448	1103	319	1221	405	10501
7	1989-90	3075	1183	799	447	1101	317	1019	403	10708
8	1990-91	3074	1189	799	446	1098	317	1290	457	10381
9	1991-92	3075	1192	801	445	1097	316	984	431	10710
10	1992-93	3075	1204	801	443	921	317	1085	416	10788
11	1993-94	3076	1217	800	444	899	316	1112	396	10790
12	1994-95	3076	1230	801	444	1048	326	1284	422	10419
13	1995-96	3062	1257	799	442	1028	320	1278	444	10420
14	1996-97	3062	1269	799	441	1017	317	1139	396	10610
15	1997-98	3063	1284	801	439	1005	313	1671	399	10075
16	1998-99	3063	1295	799	435	987	312	1266	401	10489
17	1999-00	3063	1301	796	433	979	305	1489	426	10259
18	2000-01	3068	1312	794	427	959	303	1367	409	10410
19	2001-02	3070	1325	788	423	956	302	1728	426	10031
20	2002-03	3070	1332	788	421	952	305	1832	513	9838
21	2003-04	3070	1336	788	419	947	301	1854	487	9847
22	2004-05	3070	1340	788	420	945	297	1247	443	10499
23	2005-06	3072	1349	788	419	936	292	1233	452	10509
24	2006-07	3072	1363	788	416	934	292	1565	515	10105
25	2007-08	3072	1369	788	415	930	290	1262	505	10419
26	2008-09	3072	1375	788	413	923	290	1500	516	10174
27	2009-10	3072	1386	788	413	914	288	1301	484	10404
28	2010-11	3072	1430	787	414	912	286	1199	426	10523
29	2011-12	3072	1433	787	413	908	285	1672	539	9941
30	2012-13	3073	1436	787	413	908	283	1822	535	9793
31	2013-14	3073	1444	787	411	906	281	1700	525	9923
32	2014-15	3073	1461	787	409	904	277	1572	523	10044
33	2015-16	3073	1476	793	409	907	276	1453	656	10006
34	2016-17	3073	1495	793	400	905	275	1561	692	9850
35	2017-18	3073	1480	792	399	905	271	1604	650	9874
36	2018-19	3073	1505	769	403	872	251	940	571	10664
37	2019-20	3073	1511	752	390	871	238	927	485	10802
38	2020-21	3073	1516	743	393	872	212	476	311	11453
39	2021-22	3074	1524	742	394	874	211	678	386	11166
40	2022-23	3074	1553	740	308	872	178	755	409	11161

The findings of the Table 2 come from a straightforward examination of the data presented in Table 1.

Table 2 PERCENTAGE CHANGE IN LAND USE PATTERN IN KARNATAKA (in 000' hectares)

Land Use Classification	1983-84 to 1993-94	2013-14 to 2022-23	Change	% Change
F	3030	3074	44	1%
NA	1143	1553	410	26%
B	816	740	-76	-10%
CW	485	308	-177	-57%
PP	1246	872	-374	-43%
T&G	337	178	-159	-90%
CF	919	755	-164	-22%
OF	459	409	-50	-12%
NSA	10605	11161	556	5%

Increased Categories

1. **NSA:** Increased by **556 hectares** (+5%), which indicates **expansion of agricultural activity**.
2. **NA:** Increased by **410 hectares** (+26%), this is significant increase — likely due to **urbanization**, infrastructure, or industrial expansion.
3. **F:** Small increase of **44 hectares** (+1%), suggests **relatively stable forest cover** with minor gains (could be due to afforestation or data reclassification).

Decreased Categories

1. **T&G:** 90% decreased, which is the biggest decrease. May suggest that **vegetative regions have been cleared for farming or development**.
2. **CW:** Decreased by 57%, **indicates attempts to recover marginal lands for agricultural or other uses**.
3. **PP:** 43% of it was dropped; it might have been turned **into built-up land or crops**.
4. **CF:** A 22% decrease **suggests improved land use or pressure to farm more consistently.**
5. **OF:** Small decline, that probably offset the increase in Net Sown Area or non-agricultural land.

Key Take: It is evident that more actively utilized categories like Net Sown Area and Non-Agricultural areas are replacing less productive or idle land (such as fallow, pasture, and cultivable waste). Therefore, as Net Sown Area rises, sustainable agriculture needs to be guaranteed. The intensification of agriculture and urbanization are probably the main motivators. To prevent permanent land degradation, urban expansion should be controlled. Concerns about biodiversity loss and soil degradation may arise because of the precipitous decline in trees and grooves and permanent pasture. Restoring ecological equilibrium may require tree and grassland rehabilitation.

However, this analysis is further examined and substantiated using a Markov Chain Analysis for the various land uses in Karnataka from 1984 to 2022, utilizing a transition probability matrix and a transition area matrix as in the following steps.

Step 1: Find Yearly Changes: Calculate how much land in each category changed from one year to the next. For example: Change in Forest (1983–84)=Forest (1984–85)—Forest (1984–85) = 3047–3030 = +17. For each year and each category this has been done. (Table 3)

Step 2: Separate Increases and Decreases:

- Positive changes (land area increased in that category → gains)
- Negative changes (land area decreased → losses)

For each category, all the yearly positive changes as gains and all the negative changes as losses have been summed up (Table 3).

Table 3 ESTIMATE FLOW OF LAND FROM LOSERS TO GAINERS AMONG LAND USE PATTERN IN KARNATAKA (in 000' Hectares)									
Year	**F**	**NA**	**B**	**CW**	**PP**	**T&G**	**CF**	**OF**	**NAS**
1983-84	17	6	-2	-15	-53	2	125	-14	-56
1984-85	10	9	-10	-1	-28	3	374	21	-377
1985-86	4	3	-2	-8	-8	9	-310	-49	361
1986-87	1	12	-1	-4	-21	-25	-166	1	202
1987-88	10	8	-1	-9	-33	-7	279	-12	-234
1988-89	3	1	-1	-1	-2	-2	-202	-2	206
1989-90	0	6	-1	-1	-3	0	271	54	-327
1990-91	1	3	2	-1	-1	-1	-306	-26	329
1991-92	0	12	0	-2	-176	1	101	-15	79
1992-93	1	13	-1	1	-22	-1	27	-20	2
1993-94	0	13	1	0	149	10	172	26	-371
1994-95	-14	27	-2	-2	-20	-6	-6	22	1
1995-96	0	12	0	-1	-11	-3	-139	-48	190
1996-97	1	15	2	-2	-12	-4	532	3	-535
1997-98	0	11	-2	-4	-18	-1	-405	2	414
1998-99	0	6	-3	-2	-8	-7	223	25	-230
1999-00	5	11	-2	-6	-20	-2	-122	-17	151
2000-01	2	13	-6	-4	-3	-1	361	17	-379
2001-02	0	7	0	-2	-4	3	104	87	-193
2002-03	0	4	0	-2	-5	-4	22	-26	9
2003-04	0	4	0	1	-2	-4	-607	-44	652
2004-05	2	9	0	-1	-9	-5	-14	9	10
2005-06	0	14	0	-3	-2	0	332	63	-404
2006-07	0	6	0	-1	-4	-2	-303	-10	314
2007-08	0	6	0	-2	-7	0	238	11	-245
2008-09	0	11	-1	0	-9	-2	-199	-32	230
2009-10	0	44	-1	2	-1	-2	-102	-57	119
2010-11	0	3	0	-1	-4	-1	473	112	-581
2011-12	2	3	0	-1	0	-2	151	-3	-148
2012-13	0	8	0	-2	-2	-2	-122	-10	130
2013-14	0	17	0	-1	-2	-4	-128	-2	120
2014-15	0	15	7	-1	3	-1	-118	133	-37
2015-16	0	19	0	-9	-2	-1	108	36	-156
2016-17	0	-15	-1	-1	0	-4	43	-42	24
2017-18	0	25	-23	4	-33	-20	-664	-79	790
2018-19	0	6	-17	-13	-1	-13	-13	-86	138
2019-20	0	5	-8	3	0	-26	-451	-174	651
2020-21	0	9	-1	2	2	-1	202	75	-287
2021-22	0	29	-2	-86	-2	-33	77	23	-5
Gain	**58**	**425**	**12**	**12**	**154**	**27**	**4214**	**719**	**5124**
Loss	**-14**	**-15**	**-88**	**-188**	**-528**	**-186**	**-4378**	**-769**	**-4568**

Step 3: Estimate Flow of Land from Losers to Gainers (Transition Area Matrix)

Now, it is assumed that land lost from one category flowed into categories that gained land, in proportion to their gain. That is loss category is distributed to proportionately to their gains. The cell-wise calculations in the area Transition matrix are done as below;

cell (1,1) = Share of Gain by Forest x Forest area loss = 0.54 * 14 = 7.56 ≈ 8.

cell (2,1) = Share of Gain by NA x Forest area loss = 3.96 * 14 = 55.44 ≈ 55

cell (9,9) = Share of Gain by NSA x NSA loss = 47.6862 * 4568 = 217830.56 ≈ 217831 and so on (Table 4)

Table 4 Transition Area Matrix (Area in 000' hectares)

Land Use Pattern	Loss	Gain	share of Gain	F= share * F loss	NA= share* NA Loss	B=share * B Loss	CW=share* CW Loss	PP=share * PP Loss	TG = share* TG Loss	CF=Share* CF loss	OF=share* OF loss	NSA = share* NSA loss	Total
F	14	58	0.54	**8**	**8**	**47**	**101**	**285**	**100**	**2363**	**415**	**2465**	**5793**
NA	15	425	3.96	**55**	**59**	**348**	**744**	**2089**	**736**	**17322**	**3043**	**18074**	**42470**
B	88	12	0.11	**2**	**2**	**10**	**21**	**60**	**21**	**496**	**87**	**517**	**1216**
CW	188	12	0.11	**2**	**2**	**10**	**21**	**58**	**20**	**478**	**84**	**499**	**1172**
PP	528	154	1.43	**20**	**22**	**126**	**270**	**757**	**267**	**6280**	**1103**	**6553**	**15398**
TG	186	27	0.25	**4**	**4**	**22**	**47**	**132**	**47**	**1097**	**193**	**1145**	**2690**
CF	4378	4214	39.2	**549**	**588**	**3451**	**7373**	**20707**	**7294**	**171692**	**30158**	**179143**	**420955**
OF	769	719	6.69	**94**	**100**	**589**	**1258**	**3534**	**1245**	**29302**	**5147**	**30574**	**71843**
NSA	4568	5124	47.68	**668**	**715**	**4196**	**8965**	**25178**	**8870**	**208770**	**36671**	**217831**	**511864**
TOTAL	10734	10745	100	**1400**	**1500**	**8800**	**18800**	**52800**	**18600**	**437800**	**76900**	**456800**	**1073400**

Step 4: Build Transition Matrix

The proportionate distribution to row totals of above Transition Area Matrix (Table-4) gives rise to Transition Probability Matrix as below:

Calculations for the table cells below, for instance, are;

Cell (1,1) = 8/5793 = 0.001, Cell (1,2) = 8/5793 = 0.001, Cell (2,9) = 18074/42470 = 0.426 and so on. (Table 5)

Table 5 Transition Probability Matrix

Classification of Land	F	NA	B	CW	PP	T&G	CF	OF	NSA	Total Probability
F	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
NA	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
B	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
CW	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
PP	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
T&G	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
CF	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
OF	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1
NSA	**0.001**	**0.001**	**0.008**	**0.018**	**0.049**	**0.017**	**0.408**	**0.072**	**0.426**	1

RESULTS:

The Transition Probability Matrix (TPM) reveals that a significant portion of land transitions to **Net Sown Area (42.6%)** and **Current Fallow (40.8%)**, indicate a strong agricultural and fallow land dynamics. Land use categories like **Permanent Pasture (4.9%)**, **Cultivable Waste (1.8%)**, and **Barren land (0.8%)** see lower transition rates, while **Forest** and **Non-Agricultural** areas maintain very low probabilities of transition both to and from other classes (~0.1%). Here's what each value in the first row tells from Table 6:

Table 6 Interpretation of Probabilities

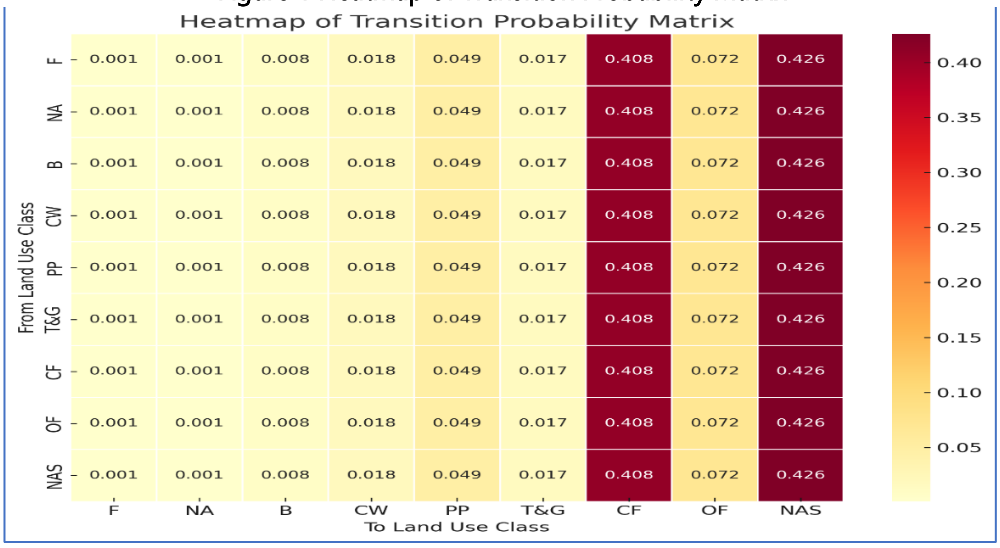
From Forest →	To	Probability	Interpretation
Forest	Forest	**0.001**	Very low probability (0.1%) that forest land remains forest — suggesting active conversion.
Forest	Non-Agricultural	**0.001**	0.1% of forest may convert to non-agricultural use (e.g., built-up areas).
Forest	Barren	**0.008**	0.8% may degrade or convert to barren land — indicating some environmental stress or land degradation.

Forest	Cultivable Waste	**0.018**	1.8% may become cultivable waste — typically fallow or degraded agricultural land.
Forest	Permanent Pasture	**0.049**	4.9% could transition to permanent pasture — perhaps indicating forest clearing for grazing.
Forest	Trees & Grooves	**0.017**	1.7% could be transformed into tree plantations or agroforestry systems.
Forest	Current Fallow	**0.408**	A very high 40.8% transition rate to fallow land suggests forest lands are frequently being cleared and then left unused temporarily.
Forest	Other Fallow	**0.072**	7.2% might convert to longer-term fallow or unproductive land.
Forest	Net Sown Area	**0.426**	The highest probability: 42.6% of forest land converts directly to cultivated area — showing deforestation for agriculture is a major land use change.

- Main conversions: Forest to Net Sown Area (42.6%) and Current Fallow (40.8%) dominate.
- Implication: Forests are being cleared at a large scale primarily for agriculture and are either immediately cultivated or temporarily left fallow.
- Environmental insight: Very low self-retention (0.1%) indicates severe forest loss and poor conservation or afforestation efforts.
- Land degradation: Small but notable transitions to barren and cultivable waste indicate environmental degradation.

Moreover, the heatmap visually encodes the probability values from the TPM using a colour gradient — typically, darker or more intense colours represent higher transition probabilities. (Figure 1)

Figure 1 Heatmap of Transition Probability Matrix



FORECASTING:
We have so far covered (1) determining the significant changes in land use categories over time and (2) calculating transition probability matrices to estimate the possibility of changes between these categories. Finally, we are using the Transition Probability Matrix to estimate future land use scenarios based on past trends using the below formula:

$$\textbf{TPM (Future)} = \sum_{k=0}^{40} \textbf{TPM}(\textbf{k})$$

As a result, the ratios for each year are determined and then averaged over the course of 40 years. The prediction values for 2024–2025 are obtained by multiplying the resulting matrix by the data for 2022–2023. (Table 8)

Table-8 Forecasting Using Transition Probability Matrix

Average Proportions of Area-40 years	**F**	**NA**	**B**	**CW**	**PP**	**TG**	**CF**	**OF**	**NSA**
	1.0004	**1.0079**	**0.9975**	**0.9892**	**0.9916**	**0.9844**	**1.0209**	**1.0040**	**1.002**
2023-24	3074.75	1553.57	740.27	308.11	872.32	178.07	755.28	409.15	11165.10
2024-25	3075.88	1554.14	740.54	308.23	872.64	178.13	755.56	409.30	11169.21
2025-26	3077.01	1554.71	740.82	308.34	872.96	178.20	755.83	409.45	11173.31
2026-27	3078.15	1555.28	741.09	308.45	873.28	178.26	756.11	409.60	11177.42
2027-28	3079.28	1555.86	741.36	308.57	873.60	178.33	756.39	409.75	11181.53
2028-29	3080.41	1556.43	741.63	308.68	873.92	178.39	756.67	409.90	11185.64
2029-30	3081.54	1557.00	741.91	308.79	874.25	178.46	756.94	410.05	11189.75
2030-31	3082.67	1557.57	742.18	308.91	874.57	178.52	757.22	410.20	11193.86

APPENDIX:

ASSUMPTIONS FOR THE MARKOV CHAIN ANALYSIS

Any sequence of trials (experiments) that can be subjected to probabilistic analysis is called a stochastic process. For a stochastic process it is assumed that the movements (transitions) of objects from one state (possible outcome) to another are governed by a probabilistic mechanism or system. A finite Markov process is a stochastic process whereby the outcome of a given trial t (t=1, 2……… T) depends only on the outcome of the preceding trial (t-1) and this dependence is the same at all stages in the sequence of trials. Consistent with this definition,

Let, S_i = be the i^{th} state of r possible outcomes; i=1, 2, ………, r

W_{it} = be the probability that state S_i occurs on trial t or the proportion observed in trial t in alternate outcome state I of the multinomial population based on a sample of size n, i.e. Pr (S_{it}).

P_{ij} = Represent the transitional probability which denotes the probability that if for any time t the process is in state S_i, it moves onto next trial to state S_j, i.e., Pr (S_j. t+1/S_{jt}) = $P_{ij.}$

P = (P_{ij}) = Represent the transitional probability matrix which denotes the transitional probability for every pair of states (i, j=1,2…………r), and has the following properties.

$$\rho_{ij} = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{n1} & \rho_{n2} & \cdots & \rho_{nn} \end{pmatrix} \quad (0 \leq \rho_{ij} \leq 1)$$

$0 < P_{ij} < 1$,………………………………………………….(1) and

$SP_{ij}=1$, for i=1, 2 …r, ……………………………………..(2)

Given this set of notations and definitions for a first order Markov chain, the probability of a particular sequence S_i on trial t and S_j on trial t+1 may be represented by

Pr (S_{it}, S_j.t+1) = Pr(S_{it}) Pr(S_j.t+1 /S_{it})= W_{it} P_{ij}. ………………. (3)

and the probability of being in state j at trial t+1 may be represented by,

Pr (S_j.t+1) = S W_{it} P_j or W_j, t+1 = S W_{it} P_{ij} . . ….. . …..… (4)

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