Annexure 1

Markov Chain model

The Markov Chain model is a data driven stochastic process that describes the probability of change from one state to another (Arsanjani *et al*., 2013). In this process, the state of a system at time t_2 is predicted depending upon the state of the system at time t_1 (Thomas and Laurence, 2006). This process consists of a key-descriptive tool, i.e. the transition probability matrix (Mousivand *et al*., 2007) which in turn provides a transition area matrix for the different mangrove classes. The transition probability matrix records the probability that each mangrove class would change to any other mangrove class (or stay the same), while the transition area matrix records the number of pixels that are expected to change from their existing mangrove class to any other mangrove class (or stay the same) over the specified number of time units (Behera *et al*., 2012). The transition area matrix, obtained from two time periods (1985-1995 and 1995-2015), was used as the basis for predicting the future mangrove species zonation and hence the carbon stock scenario.

In the Markov chain model, a chain represents a stochastic process at time *t*, X_t, which exclusively depends on the value at time *t-1*, i.e. X_{t-1}, and not depending on the previous series of values (i.e. X_{t-2}, X_{t-3}……..X_0), and the transition probability equation may be written as (Weng,2002)

$$P\left\{X_t = a_j \middle| X_0 = a_0, X_1 = a_1, ..., X_{t-1} = a_i\right\} = P\left\{X_t = a_j \middle| X_{t-1} = a_i\right\} \quad (1)$$

The mathematical expression $P\left\{X_t = a_j \middle| X_{t-1} = a_i\right\}$ is termed as the one-step transitional probability, i.e. the possibility of the transition from state a_i to state a_j over one time period. If

ℓ steps are required to implement this transition, the expression $P\{X_t = a_j | X_{t-1} = a_i\}$ is called the ℓ step transition probability, $P_{ij}^{(\ell)}$.

When $P_{ij}^{(\ell)}$ is time independent and is dependent only on a_i, a_j and ℓ, then the Markov Chain is regarded as homogeneous, i.e.

$$P\{X_t = a_j | X_{t-1} = a_i\} = P_{ij} \quad (2)$$

where P_{ij} is derived from the observed data, after determination of the number of times the observed data goes from state *i* to *j*, n_{ij}, and the number of occurrences of the state a_i, n_i is summed up. Then the equation becomes,

$$P_{ij} = n_{ij} / n_i \quad (3)$$

As the Markov Chain proceeds, the probability of remaining in the state *j* becomes independent of the initial state of the chain after many steps. As this condition is achieved, the chain is believed to have attained a steady state and accordingly P_j, i.e., the limit probability, is applied for the determination of the value of $P_{ij}^{(\ell)}$ according to the equation

$$\lim_n P_{ij}^{(n)} = P_j \quad (4)$$

where, $P_j = P_i P_{ij}^{(n)}$ $j=1, 2, \ldots, m$ (state); $P_i = 1$; $P_j > 0$

In the case of transition probability matrix, each of the elements consist of a category with observed and expected number of transitions as per the equation

$$\chi^2 = \sum \frac{(O-E)^2}{E} \quad (5)$$

Here *O* is the observed number of transitions from one state to another and *E* is the expected number of transition; in each case, the successive states are independent.

Cellular automata

The principle upon which the Markov Chain model works, is not at all influenced by the state of the neighbour cells; it is only dependent on the state of a particular cell under observation at time t_1 and t_2 (Eastman, 2006). This is why the Markov Chain model by itself cannot solve the entire problem, since it does not take into account the spatial distribution within each category. Hence it might depict the correct magnitude of change; however it is not capable of showing the right direction (Boerner *et al*., 1996). In order to incorporate the spatial attribute and hence direction to the present modelling, the Cellular Automata (CA) model is implemented (Soe and Le, 2006). One of the most crucial geospatial elements that principally governs and regulates the variability of the change events is proximity (Arsanjani *et al*., 2013). A cellular automaton (in the present context, a pixel or a mangrove class) is considered to be an entity that independently varies its state not only based on its pre-existing state but also on the state of its immediate neighbours (i.e. the most proximal classes) (Clarke and Gaydos, 1998). The overall performance of the system is decided from the combined actions of all the locally defined transition rules; therefore, the state of the system moves forward in discrete time steps.

Thus the spatial and temporal attributes of the prediction made in this study is achieved by the fusion of Markov chain model and the Cellular automata (CA) model. The CA model with powerful spatial computing was used to simulate the spatial variation of the system effectively (Kamusoko *et al*., 2009), while the CA–Markov model was used to achieve better simulation for temporal and spatial patterns of land class changes in quantity and space (Sang *et al*., 2011).

At first, the preceding state transition rules have been calculated using Markov Chain methods. The calculated transition probability matrix so obtained serves as the transformation rules in the CA–Markov model simulations. CA filters are known to produce a clear sense of

the spatial weighting factor, which can be changed according to the current adjacent cellular state. The standard 5 * 5 contiguity filter has been used as the neighbourhood definition in this study, which means that each cellular centre is surrounded by a matrix space, which is composed of 5 * 5 cells to impact the cellular changes significantly.

Annexure 2

Comparison of total carbon stock with other mangrove ecosystems

Various types of predictive modelling based studies have been conducted on mangrove stands throughout the world. Population dynamics of *Avicennia marina* stands were predicted taking into account small- and large-scale possible perturbations to the ecosystem in south-eastern Australia (Clarke, 1995). The effect of sea level rise was predicted on the mangroves of north-western Australia (Semeniuk, 1994). Several studies were focused on limitations and advances of predicting mangrove dynamics and deforestation (Berger *et al*., 2008; Rideout et al., 2013). However, in recent times very few studies have been reported on predicting the dominance, expanse and variability of the distribution of species assemblages like that of Crase *et al*. (2015) and Cavanaugh *et al*. (2015). The present study is framed with a different approach where the species assemblage dynamics is predicted simply in a business as usual mode; i.e. how the species assemblage would vary spatially and temporally is predicted based on the way it has varied in the past decades. Moreover, this study has generated a gross total blue carbon stock estimate for the Bangladesh Sundarban. Most of the carbon stock assessment studies carried out on mangroves produced their final results in terms of carbon mass per unit area; however total carbon stock is assessed by a few of them. The estimated total carbon stock of this ecosystem was found to be the highest compared to the recent assessments made (Table 3). In the Indian part of the Sundarban, Ray *et al*. (2011) found a much lower total carbon stock of 26.62 Tg (however, they took into account the soil organic carbon only up to a depth of 30 cm; which implies a substantial part of carbon stock is not measured in this part). Total carbon stock was high in the stands of Sian Ka'an biosphere reserve, Mexico (43.2 Tg – 58.0 Tg; Adame *et al*., 2013). The mangroves of entire China at present constitute 6.91 Tg C (Liu *et al*., 2014), whereas only the carbon locked in the above-

ground part of entire Mozambique's mangroves amounts to 11.8 Tg (Fatoyinbo *et al*., 2008). It is quite obvious that the total stock of carbon would be greater in places where the stretch of the forest covers larger areas and since the Sundarban of Bangladesh happens to be one of the largest single expanses of contiguous mangrove forest it was expected to have a giant mass of carbon. However, it is evident from the ratio of total stock to total area (given in Table 3) that the carbon content per unit area varied substantially between these mangrove forests. This spatial variability in the carbon stock of mangroves based on geographical locations arises due to various aspects, like the age of the forest (Kridiborworn *et al*., 2012), species diversity and dominance (Ksawani *et al*., 2007), health and stature of above-ground vegetation (Murdiyarso *et al*., 2010) and wood density (Baker *et al*., 2004). It also depends on factors like mineral content of the sediment (Crooks et al. 2011) along with the quality and quantity of the peat soil (Siikamäki *et al*., 2012).On the whole this comparative assessment signifies the importance of Bangladesh Sundarban (in terms of its total carbon reservoir) with respect to the global mangrove cover.

Table S1 The carbon content in the above-ground (AG) trunk and stems and below-ground (BG) root system of the major genus found in the Bangladesh Sundarban

Species Name	AG (%)	BG (%)
Avicennia spp.	48.6 ± 1.5	45.3 ± 1.4
Bruguiera spp.	51.3 ± 2.6	47.5 ± 1.9
Ceriops spp.	53.6 ± 0.8	46.5 ± 1.1
Excoecaria spp.	54.8 ± 0.7	52.6 ± 0.4
Heritiera spp.	50.1 ± 0.9	52.4 ± 0.7
Sonneratia spp.	52.7 ± 0.6	49.2 ± 0.7
Xylocarpus spp.	51.4 ± 0.9	48.5 ± 1.1

Table S2 Comparison of blue carbon stock from the current study with other mangroves of the world measured in recent times

Site	Total blue carbon stock in Tg (total area in km^2)	Remarks	Source
Bangladesh Sundarban	91.19 Tg (3659)	-	Present study
Indian Sundarban	26.62 Tg (1781)	Soil carbon measured up to 30 cm depth only	Ray *et al*. (2011)
Sian Ka'an Biosphere reserve, Mexico	43.2 to 58.0 Tg (1722)	Soils contained 78% to 99% of total ecosystem carbon	Adame *et al*. (2013)
Mangroves of entire Mozambique	11.80 Tg* (2909)	*Only the above-ground carbon content is measured	Fatoyinbo *et al*. (2008)
Mangroves of entire China	6.91 Tg (220)	The potential of carbon stock can be increased to 28.81 Tg	Liu *et al*. (2014)
Yap and Palau Island groups of Micronesia	4.85 Tg (54)	Mangroves cover only 12-13% of these island's total area	Donato *et al*. (2012)
Montecristi Province in the Northwest Dominican Republic	3.67 Tg (92)	Rich carbon deposits found up to depths of 2 m	Kauffman *et al*. (2014)
Matang mangrove forest reserve, Peninsular Malaysia	2.15 Tg (410)	Earlier in 1991 it was 3.04 Tg	Hamdan *et al*. (2013)
San Juan, Batangas	0.012 Tg (1)	Expected to increase up to 0.025 Tg after rehabilitation of mangroves	Gevaña et al. (2008)

References

Adame MF, Kauffman JB, Medina I, Gamboa JN, Torres O, Caamal JP, Reza M (2013) Carbon stocks of tropical coastal wetlands within the karstic landscape of the Mexican Caribbean. PLoS One 8:e56569. doi:10.1371/journal.pone.0056569

Arsanjani JJ, Helbich M, Kainz W, Boloorani AD (2013) Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. International Journal of Applied Earth Observation and Geoinformation 21:265-275

Baker TR, Phillips OL, Malhi Y, Almeida S, Arroyo L, Di Fiore A, Erwin T, Killeen TJ, Laurance SG, Laurance WF, Lewis SL, Lloyd J, Monteagudo A, Neill DA, Patino S, Pitman NCA, Silva JNM, Martinez RV (2004) Variation in wood density determines spatial patterns in Amazonian forest biomass. Global Change Biology 10:545–562.

Behera MD, Borate SN, Panda SN, Behera PR, Roy PS (2012) Modelling and analyzing the watershed dynamics using cellular automata (CA)-Markov model- A geo-information based approach. Journal of Earth System Science 121:1011-1024

Berger U, Rivera-Monroy VH, Doyle TW, Dahdouh-Guebas F, Duke NC, Fontalvo-Herazo ML, Hildenbrandt H, Koedam N, Mehlig U, Piou C, Twilley RR (2008) Advances and limitations of individual-based models to analyze and predict dynamics of mangrove forests: A review. Aquatic Botany 89:260-274.

Boerner DE, Kurtz RD, Craven JA (1996) Electrical conductivity and Paleo-Proterozoic foredeeps. Journal of Geophysical Research 101:13775–13791

Cavanaugh KC, Parker JD, Cook-Patton SC, Feller IC, Williams AP, Kellner JR (2015) Integrating physiological threshold experiments with climate modelling to project mangrove species' range expansion. Global Change Biology 21:1928-1938.

Clarke KC, Gaydos LJ (1998) Loose-coupling a cellular automaton model and GIS:long-term urban growth prediction for San Francisco and Washington/Baltimore. International Journal of Geographical Information Science 12:699–714.

Clarke PJ (1995) The population dynamics of the mangrove *Avicennia marina*; demographic synthesis and predictive modelling. In: Asia-Pacific Symposium on Mangrove Ecosystems (eds Wong S, Tam NEY) pp. 83-88, Springer Netherlands.

Crase B, Vesk PA, Liedloff A, Brendan WA (2015) Modelling both dominance and species distribution provides a more complete picture of changes to mangrove ecosystems under climate change. Global Change Biology.doi: 10.1111/gcb.12930

Crooks S, Herr D, Tamelander J, Laffoley D, Vandever J (2011) Mitigating climate change through restoration and management of coastal wetlands and near-shore marine ecosystems: challenges and opportunities. Environment Department Paper 121, World Bank, Washington, DC.

Donato DC, Kauffman JB, Mackenzie RA, Ainsworth A, Pfleeger AZ (2012) Whole-island carbon stocks in the tropical Pacific: Implications for mangrove conservation and upland restoration. Journal of Environmental Management 97:89-96.

Eastman JR (2006) IDRISI 15: The Andes edition. Clark University, Worcester, MA.

Fatoyinbo TE, Simard M, Washington-Allen RA, Shugart HH (2008) Landscape-scale extent, height, biomass, and carbon estimation of Mozambique's mangrove forests with Landsat ETM+ and Shuttle Radar Topography Mission elevation data. Journal of Geophysical Research: Biogeosciences (2005–2012) 113, G02S06. doi:10.1029/2007JG 000551.

Gevaña DT, Pulhin FB, Pampolina NM (2008) Carbon stock assessment of a mangrove ecosystem in San Juan, Batangas. Journal of Environmental Science and Management 11:15-25.

Hamdan O, Khairunnisa MR, Ammar AA, Hasmadi IM, Aziz HK (2013) Mangrove carbon stock assessment by optical satellite imagery. Journal of Tropical Forest Science 25:554-565.

Kamusoko C, Aniya M, Adi B, Manjoro M (2009) Rural sustainability under threat in Zimbabwe – Simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Applied Geography 29:435-447.

Kauffman JB, Heider C, Norfolk J, Payton F (2014) Carbon stocks of intact mangroves and carbon emissions arising from their conversion in the Dominican Republic. Ecological Applications 24:518–527

Kridiborworn P, Chidthaisong A, Yuttitham M, Tripetchkul S (2012) Carbon sequestration by mangrove forest planted specifically for charcoal production in Yeesarn, Samut songkram. Journal of Sustainable Energy and Environment 3:87–92.

Ksawani I, Kmarusaman J, Nurum-Nadhirah MI (2007) Biological diversity assessment of Tok Bali mangrove forest, Klantan, Malaysia. WSEAS Transactions on Environment and Development 3 :7–44.

Liu H, Ren H, Hui D, Wang W, Liao B, Cao Q (2014) Carbon stocks and potential carbon storage in the mangrove forests of China. Journal of Environmental Management 133:86-93.

Mousivand AJ, Alimohammadi Sarab A, Shayan S (2007) A new approach of predicting land use and land cover changes by satellite imagery and Markov chain model (Case study: Tehran). MSc Thesis. TarbiatModares University, Tehran, Iran.

Murdiyarso D, Donato D, Kauffman JB, Kurnianto S, Stidham M, Kanninem M (2010) Carbon storage in mangrove and peat land ecosystems—a preliminary account from plots in Indonesia, CIFOR Working Paper no. 48, Center for International Forestry Research (CIFOR), Bogor, Indonesia, pp. 35.

Ray R, Ganguly D, Chowdhury C, Dey M, Das S, Dutta MK, Mandal SK, Majumder N, De TK, Mukhopadhyay SK, Jana TK (2011) Carbon sequestration and annual increase of carbon stock in a mangrove forest. Atmospheric Environment 45:5016-5024.

Rideout AJ, Joshi NP, Viergever KM, Huxham M, Briers RA (2013) Making predictions of mangrove deforestation: a comparison of two methods in Kenya. Global Change Biology 19:3493-3501.

Sang L, Miller JJ, Corbit KC, Giles RH, Brauer MJ, Otto EA, Baye LM, Wen X, Scales SJ, Kwong M, Huntzicker EG, Sfakianos MK, Sandoval W, Bazan JF, Kulkarni P, Garcia-Gonzalo FR, Seol AD, O'Toole JF, Held S, Reutter HM, Lane WS, Rafiq MA, Noor A, Ansar M, Devi AR, Sheffield VC, Slusarski DC, Vincent JB, Doherty DA, Hildebrandt F, Reiter JF, Jackson PK (2011) Mapping the NPHP-JBTS-MKS protein network reveals ciliopathy disease genes and pathways. Cell 145:513-528.

Semeniuk V (1994) Predicting the effect of sea-level rise on mangroves in northwestern Australia. Journal of Coastal Research 10:1050-1076.

Siikamäki J, Sanchirico JN, Jardine SL (2012) Global economic potential for reducing carbon dioxide emissions from mangrove loss. Proceedings of the National Academy of Sciences, 109:14369–14374.

Soe WM, Le W (2006) Multicriteria decision approach for land use and land cover using Markov chain analysis and a cellular automata approach. Canadian Journal of Remote Sensing 32:390-404.

Thomas H, Laurence HM (2006) Modelling and projecting land-use and land-cover changes with a cellular automaton in considering landscape trajectories: An improvement for simulation of plausible future states. EARSeL eProc 5:63-76.

Weng QH (2002) Land use change analysis in the Zhujing Delta of China using satellite remote sensing, GIS and stochastic modeling. Journal of Environmental Management 64:273-284.