CLIMATE CHANGE IN BANGLADESH: A SUSTAINABLE DEVELOPMENT PERSPECTIVE

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Abstract

Bangladesh is at the frontline of the battle against climate change, which directly threatens the economic development prospects of the country. This paper utilises expectation maximisation algorithms and autoregressive integrated moving average models to predict the state of climate change indicators for Bangladesh in the near future. The findings from the forecasts show that in the business-as-usual scenario, annual average temperatures will increase by 0.95 per cent, greenhouse gas emissions will increase 5.17 per cent and a total of 30,366,230 households will be affected by climate change in Bangladesh in 2030. Therefore, anthropogenic climate change is increasing the probability of natural disasters which have grave consequences for Bangladesh. Hence, the gulf between the rhetoric and reality of climate change needs to be narrowed down urgently. A number of policy measures are recommended to tackle the risks of climate change in Bangladesh.

Keywords: sustainable development, climate change, Bangladesh

JEL classification: O10, O20, Q01

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1. INTRODUCTION

Since South Asian countries constitute of a substantial portion of the world's poor and impoverished people, the region plays a pivotal role in the success, or lack thereof, of the implementation of the SDGs in the world. Bangladesh is a low-lying delta country from South Asia, which bears the brunt of climate change due to its geographical location, land characteristics, riverine nature and monsoon climate. According to the Climate Risk Index 2017, Bangladesh is among the 10 most climate change affected countries across the world. Among the commonly occurring natural disasters in the country, while river bank erosion and salinity intrusion are often talked about, cyclones and floods are known to cause damage on a colossal scale. Frightening numbers of the poor are concentrated along rivers and estuaries, the Barind Tract area in the North-West, and in the Southwestern coastal belt where the Sundarbans mangrove forest lies.

Augmenting agricultural production and improving livelihoods in the areas affected by climate change remains a major challenge. According to Intergovernmental Panel on Climate Change (IPCC), in a low crop productivity scenario, Bangladesh would experience a net increase in poverty of 15% by 2030 due to climate change. 17% people of the country will need to be relocated if global warming persists at the present rate. 81% migrants in Dhaka's slums reported a climate-related cause for displacement. It has been predicted that there will be 3 to 10 million internal migrants in Bangladesh over the next 40 years, depending on the severity of climate change. According to the World Bank, climate change will cost Bangladesh USD 121 billion during 2005-2050, or USD 3 billion annually, unless measures are taken.

2030 Agenda has put a lot of performance demands on the country due to its extremely ambitious and all-encompassing nature, owing to its economic, social, and environmental aspects. Through its central pledge of Leave No One Behind, the 2030 Agenda addresses vulnerable groups in society. 2030 Agenda also addresses climate change and disaster-risk reduction and resilience (endorsing the Paris Agreement and the Sendai Framework). SDG target 13.a calls upon developed countries to jointly mobilise USD 100 billion annually by 2020 from all sources to address the needs of developing countries in the context of meaningful mitigation actions and transparency on implementation and fully operationalise the Green Climate Fund through its capitalisation as soon as possible. Advanced economies formally agreed within the Paris Agreement to mobilise at least USD 100 billion per year by 2020. Globally, pledges worth USD 10.2 billion towards the Green Climate Fund (GCF) were signed in 2018.

In 2018, Bangladesh was declared eligible for graduating from the least development countries (LDCs) to the developing nation category. According to UN's graduation thresholds: i)Gross National Income (GNI) per capita of a country should be USD 1,230 or above (Bangladesh's GNI per capita was USD 1,610 towards the end of FY2016-17); ii) Human Assets Index (HAI) score must be 66 or above (Bangladesh scored 72.9 in HAI); and iii) Economic Vulnerability Index (EVI) score must be 32 or below (Bangladesh scored 24.8 in EVI). When Bangladesh was declared to be eligible for LDC graduation, it had a 7-point margin over the threshold EVI. However, if Bangladesh's environmental vulnerability increases due to climate change, then the country's EVI may increase, which will jeopardise its prospects of LDC graduation by 2024.

In this backdrop, this research aims to fill in the gap in the knowledge on the SDG implementation progress and prospects in Bangladesh. Therefore, this research represents an avant-garde contribution to the knowledge on SDG implementation in Bangladesh that may be used as a prototype for creating similar studies for other countries. This study has 3 research objectives: i) to describe the progress of SDG implementation in Bangladesh; ii) to forecast the prospects of SDG implementation in Bangladesh; and iii) to recommend policies for the SDGs which are at risk of remaining unattained in Bangladesh in 2030.

Forecasting the prospects of SDG implementation is critically important for Bangladesh, which is determined to carry forward its impressive development record of the past. Forecasting is necessary to determine whether a certain future event or outcome will occur, so that adequate measures may be taken at present (Makridakis, Wheelwright, & Hyndman, 1997). Forecasting is a tool for effective and efficient planning (Hyndman & Athanasopoulos, 2018) which can aid in the attainment of goals. Forecasts can be used for scheduling, acquiring resources, or determining resource requirements (Makridakis, Wheelwright, & Hyndman, 1997). Therefore, by predicting the trajectory of selected indicators, we can better understand the actions required to attain the SDGs and plan accordingly.

The remainder of this paper is structured as follows: Section 2 contains an overview of the trends in key SDG indicators of Bangladesh, which shed light on the performance of the country vis-à-vis SDG implementation. Following this, Section 3 explains the statistical and econometric methodology used in analysing the data. Section 4 summarizes the results of the data analysis and gives a bird’s eye view of the future of SDG implementation in Bangladesh.

Finally, Section 5 ends the chapter with a few concluding remarks and policy recommendations.

2. PAST PROGRESS

Bangladesh is one of the countries of the world which are most vulnerable to climate change. The number of households affected by natural disasters in Bangladesh has increased from 550,555 in 2009 to 1,934,629 in 2014 (BBS, 2015a). This implies that as high as 44.36 per cent of all households in Bangladesh were affected by natural disasters. During the period 2009 to 2014, the total number of households affected by natural disasters increased in five of the seven geographic divisions (Figure 1 A-H).

Figure 1 (A-H): Number of households affected by natural disasters, by division and type of disaster

Figure 1A: Number of households affected by disasters (National)

Figure 1B: Number of households affected by disasters (Barisal)

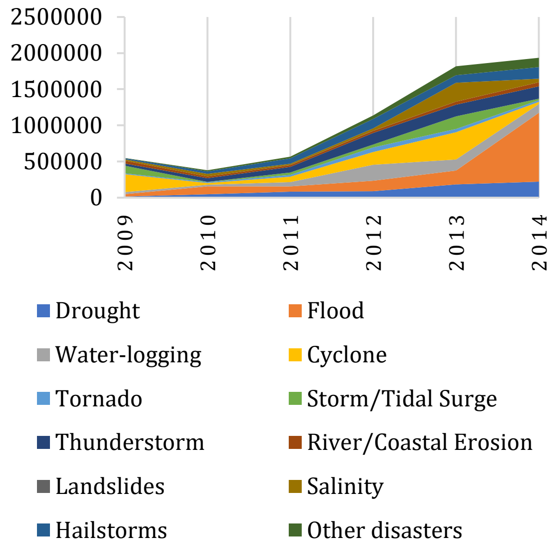


Figure 1C: Number of households affected by disasters (Chittagong)

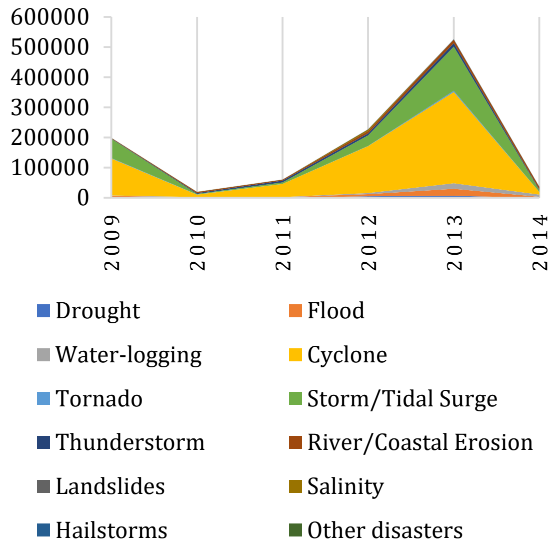


Figure 1D: Number of households affected by disasters (Dhaka)

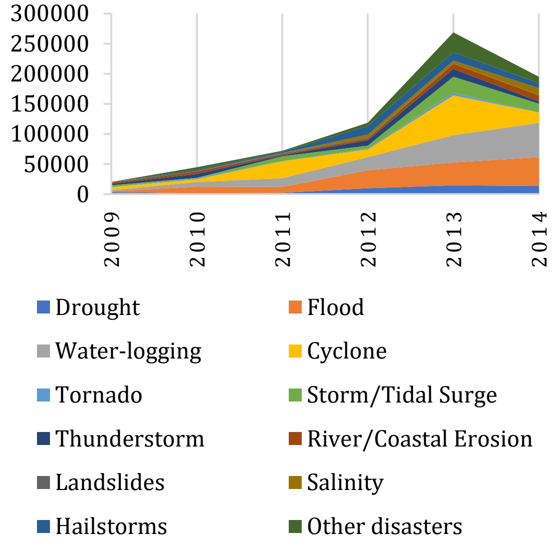


Figure 1E: Number of households affected by disasters (Khulna)

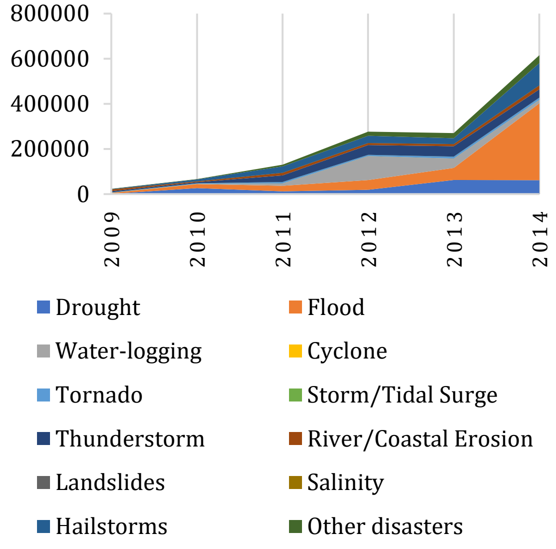
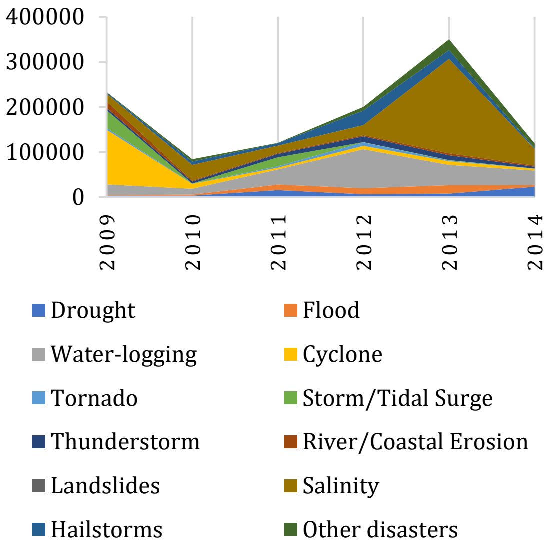


Figure 1F: Number of households affected by disasters (Rajshahi)



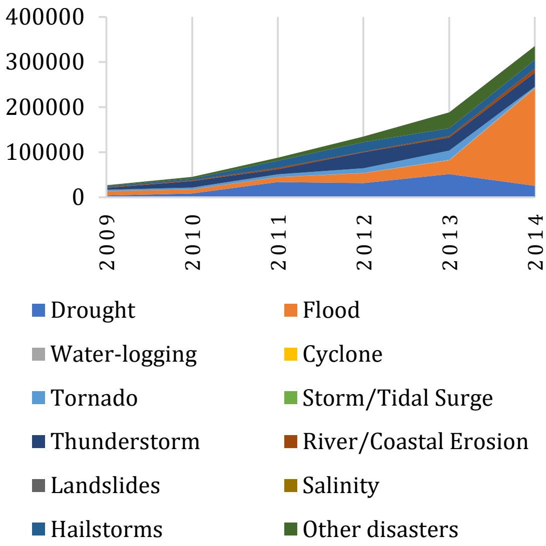
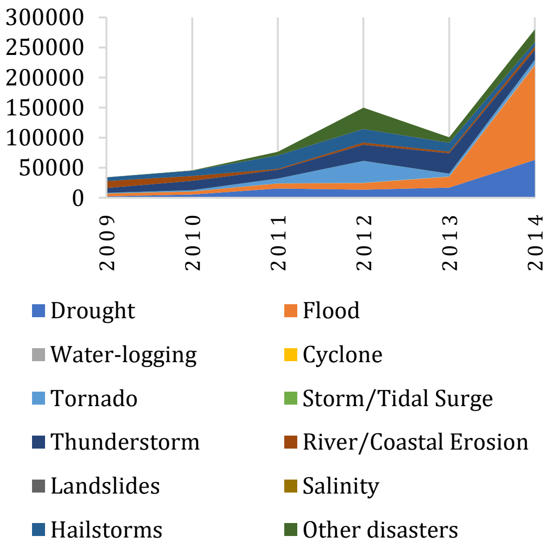
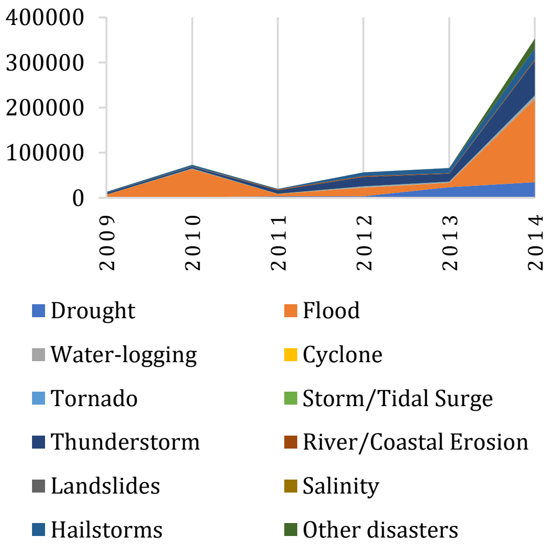


Figure 1G: Number of households affected by disasters (Rangpur)

Figure 1H: Number of households affected by disasters (Sylhet)





Source: Authors' illustration based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

Note: Household is defined as a group of people who share the same kitchen, including single persons.

Floods affected 1,503,742 households or 34.48 per cent of all households in Bangladesh during the period 2009 to 2014, which was the highest among all the type of disasters (BBS, 2015a). In Dhaka, Rajshahi, Rangpur and Sylhet division, floods were the most common natural disaster, although in Barishal division cyclones were more common and in Khulna division cyclones and salinity were major concerns during the period 2009-2014 (BBS, 2015a) (Table 1).

Table 1: Proportion of households affected by natural disasters, by division and type of disaster (in percentage) (2009-2014)

	Drought	Flood	Water logging	Cyclone	Tornado	Storm/Tidal Surge	Thunderstorm	River/Coastal Erosion	Landslides	Salinity	Hailstorm	Other disasters
National	14.80	34.48	13.88	21.31	4.14	8.65	14.94	4.95	0.08	4.09	11.88	7.90
Barisal	1.41	5.24	3.91	78.31	0.91	31.51	3.72	4.35	0.00	0.85	0.31	0.05
Chittagong	10.61	32.03	34.39	30.96	1.80	13.51	8.39	7.01	0.80	5.30	9.46	12.86
Dhaka	19.89	51.89	18.68	0.00	3.88	0.00	17.69	6.42	0.00	0.00	20.86	9.27
Khulna	9.30	7.68	34.88	23.23	2.62	9.16	7.39	4.15	0.00	22.24	10.31	7.32
Rajshahi	25.39	48.47	0.65	0.00	7.51	0.00	20.40	3.39	0.00	0.00	12.86	14.73
Rangpur	23.99	41.74	0.68	0.00	12.30	0.00	23.53	6.87	0.00	0.00	16.62	8.34
Sylhet	16.51	69.97	2.57	0.00	1.30	0.00	31.84	1.95	0.02	0.00	12.54	5.42

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

Note: Household is defined as a group of people who share the same kitchen, including single persons.

The total economic loss due to natural disasters during the period 2009-2014 was BDT 184247.34 million (BBS, 2015a). Sector-wise disaggregation shows that crops suffered the greatest economic loss due to natural disasters during the period 2009 to 2014, which amounted to BDT 66703.42 million (BBS, 2015a) (Table 2).

Table 2: Economic loss due to natural disasters in million BDT, by sector and type of disaster (2009-2014)

	All sectors	Crops	Livestock	Poultry	Fishery	Land	Houses	Homestead & Forestry
All natural disasters	184247.34	66703.42	8772.16	2224.88	10713.99	49229.73	31676.89	14926.27
Drought	10569.20	9144.99	191.14	81.93	189.65	698.15	0.00	263.34
Flood	42807.19	22163.26	2373.29	593.81	1986.77	8966.45	5040.03	1683.58
Water logging	16062.24	8660.70	702.99	204.59	2466.43	1541.53	1769.64	716.36
Cyclone	28384.81	4194.25	3137.51	750.92	2109.46	0.00	10833.38	7359.29
Tornado	4299.03	984.46	145.80	28.02	0.00	0.00	2484.62	656.13
Storm or tidal surge	12676.02	2343.78	769.93	321.96	3271.24	3318.00	1847.69	803.42
Thunderstorm	10940.12	2493.63	432.28	103.39	0.00	0.00	6212.35	1698.47
River or coastal erosion	36408.92	1076.20	729.30	33.90	338.72	31742.12	2034.28	454.40
Landslides	249.01	7.78	0.16	0.11	0.00	200.23	21.44	19.29
Salinity	6072.94	2162.73	142.23	11.01	0.00	2763.21	46.92	946.84
Hailstorm	11471.69	9679.63	53.38	27.01	0.00	0.00	1386.53	325.14
Other natural disasters	4306.11	3792.00	94.14	68.24	351.73	0.00	0.00	0.00

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

On the other hand, Dhaka division suffered economic losses due to natural disasters equivalent to BDT 46055.30 million during the period 2009-2014, which was the greatest among all the geographic divisions of the country (BBS, 2015a) (Table 3).

Table 3: Economic loss due to natural disasters in million BDT, by division and type of disaster (2009-2014)

	National	Barisal	Chittagong	Dhaka	Khulna	Rajshahi	Rangpur	Sylhet
All natural disasters	184247.34	36974.39	19029.86	46055.30	29212.54	21690.37	15614.68	15670.23
Drought	10569.20	70.33	476.45	2938.59	753.97	2663.93	2049.42	1616.54
Flood	42807.19	1028.85	3327.15	14490.14	1627.01	7811.03	5209.37	9313.71
Water logging	16062.24	696.42	2955.37	4188.42	7907.72	59.16	80.91	174.25
Cyclone	28384.81	19827.45	3358.18	0.00	5199.17	0.00	0.00	0.00
Tornado	4299.03	245.48	236.89	872.74	420.96	1035.58	1056.96	130.41
Storm or tidal surge	12676.02	9285.54	999.72	0.00	2390.77	0.00	0.00	0.00
Thunderstorm	10940.12	241.42	1411.20	3069.49	769.74	2059.35	1462.44	1926.44
River or coastal erosion	36408.92	5276.16	3905.81	14175.58	3221.95	4926.18	4085.82	817.40
Landslides	249.01	0.00	248.96	0.00	0.00	0.00	0.00	0.05
Salinity	6072.94	284.07	650.34	0.00	5138.54	0.00	0.00	0.00
Hailstorm	11471.69	17.83	684.08	5314.29	1021.23	1599.98	1323.12	1511.13
Other natural disasters	4306.11	0.87	475.68	1006.08	761.42	1535.16	346.62	180.28

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

Children were disproportionately affected by climate change as 69.53 per cent of individuals who fell sick due to natural disasters during 2009 to 2014 were 17 years old or younger

(BBS, 2015a). On the other hand, adults were the most prone to injury, as 47.33 per cent of individuals aged 18 to 60 suffered from injury due to natural disasters during 2009 to 2014 (BBS, 2015a) (Table 4).

Table 4: Proportion of individuals suffering from sickness and injury due to natural disasters, by division and age group (as a percentage of relevant group) (2009-2014)

	Sickness				Injury			
	Total	Age 00–17	Age 18–60	Age 61+	Total	Age 00–17	Age 18–60	Age 61+
National	100.00	69.53	25.83	4.63	100.00	36.54	47.33	16.13
Barisal	12.12	9.21	2.27	0.65	13.04	3.72	5.04	4.28
Chittagong	12.65	8.86	3.27	0.52	17.80	6.45	8.19	3.17
Dhaka	20.97	15.09	4.58	1.29	15.43	4.74	8.23	2.46
Khulna	12.97	7.62	4.54	0.82	16.09	3.85	8.96	3.28
Rajshahi	16.17	10.73	4.79	0.64	15.89	6.66	7.94	1.29
Rangpur	12.07	8.44	3.27	0.35	9.26	4.55	3.68	1.03
Sylhet	13.04	9.58	3.10	0.36	12.49	6.58	5.30	0.61

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

In terms of natural disasters, floods had the most damaging impact on human life as 47.91 per cent of all individuals suffered from sickness and 41.90 per cent of all individuals suffered from an injury due to floods (BBS, 2015a) (Table 5).

Table 5: Proportion of individuals suffering from sickness and injury due to natural disasters, by type of disaster and age group (as a percentage of relevant group) (2009-2014)

	Sickness				Injury			
	Total	Age 00–17	Age 18–60	Age 61+	Total	Age 00–17	Age 18–60	Age 61+
All disasters	99.99	69.53	25.83	4.63	100.00	36.54	47.33	16.13
Drought	7.07	4.71	2.03	0.33	0.00	0.00	0.00	0.00
Flood	47.91	33.76	12.24	1.91	41.90	19.87	17.94	4.09
Water logging	12.42	8.45	3.29	0.68	7.67	1.77	4.39	1.51
Cyclone	12.07	8.44	2.91	0.72	15.21	4.32	5.34	5.55
Tornado	1.19	0.86	0.28	0.05	8.42	2.05	5.29	1.08
Storm or tidal surge	4.56	3.08	1.27	0.21	3.87	0.76	2.39	0.72
Thunderstorm	4.75	3.71	0.92	0.12	6.69	2.60	3.63	0.46
River or coastal erosion	0.85	0.55	0.22	0.08	4.16	2.01	1.64	0.51
Landslides	0.04	0.02	0.02	0.00	0.01	0.00	0.01	0.00
Salinity	0.80	0.36	0.41	0.03	0.00	0.00	0.00	0.00
Hailstorm	3.49	2.24	0.97	0.28	9.09	1.93	5.53	1.63
Other disasters	4.84	3.34	1.27	0.23	3.00	1.23	1.17	0.60

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

Average annual economic loss per household due to natural disasters was estimated to be BDT 7040 per year or around 5.1 per cent of average annual household income during the period 2009 to 2014 (BBS, 2015a). However, these losses were not equally shared among all households. Average annual economic loss per households due to natural disasters was as high as 15.7 per cent of average annual household income for the poorest quintile oh households, but only 3.1 per cent of average annual household income for the richest quintile of households. Thus, the poorest households were disproportionately affected by climate change-induced natural disasters during the period 2009 to 2014 (BBS, 2015a) (Table 6).

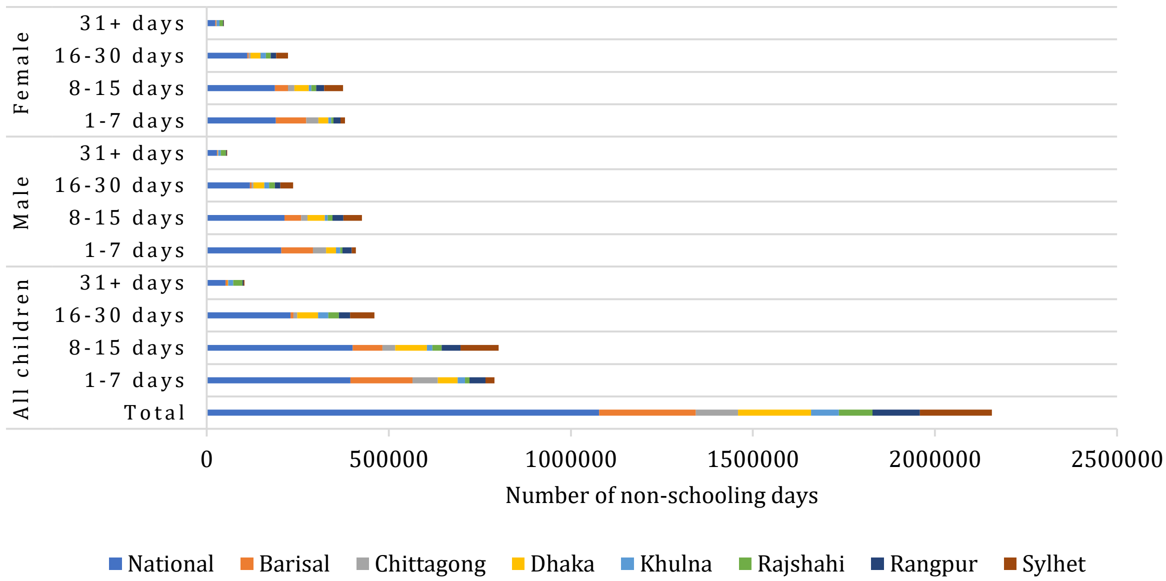
Table 6: Average annual economic loss per household due to natural disasters, by household income quintile groups and type of loss (in BDT)

Quintile	Average annual household income (in BDT)	Crops	Livestock	Poultry	Fishery	Land	Houses	Homestead & forestry	Total	Economic loss as a proportion of household income
1	34957	2038	279	75	268	1351	1066	394	5471	15.7%
2	74590	1776	270	77	220	1397	1231	382	5353	7.2%
3	105986	1987	331	87	300	1888	1255	529	6377	6%
4	152092	2566	353	92	395	2026	1260	743	7435	4.9%
5	357897	4665	460	95	934	2877	1244	846	11121	3.1%
Average	139357	2549	335	85	409	1881	1211	570	7040	5.1%

Source: Authors' compilation based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

In the aftermath of a natural disaster, there is often widespread damage to infrastructure and disruptions of transportation links. As a result, children may not be able to travel to their schools, or even worse, the schools themselves may be destroyed. Additionally, schools in remote rural areas of Bangladesh are often utilized as storm shelters, which means that sometimes classes cannot continue during inclement weather. During the period from 2009 to 2014, children in Bangladesh missed a total of 1,078,118 days of school due to natural disasters (BBS, 2015a). Boys missed school marginally more than girls and children in Barishal division were the worst affected due to natural disasters (BBS, 2015a) (Figure 2).

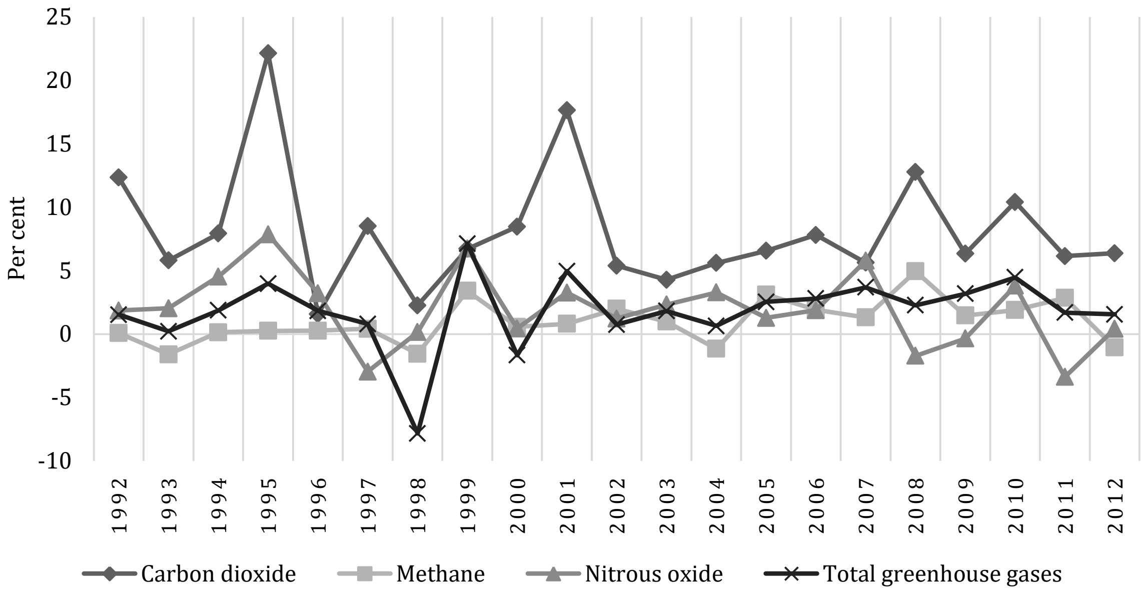
Figure 2: Number of days children missed school due to natural disasters, by division and gender (2009-2014)



Source: Authors' illustration based on Bangladesh Disaster-Related Statistics 2015 (BBS, 2015a).

Per capita emissions in Bangladesh are generally much lower than those in developed countries. Nevertheless, with rapid economic advancement, emission have been growing in recent years. On average, carbon dioxide emissions increased at 8.11 per cent, while methane and nitrous oxide emissions increased by 0.99 per cent and 1.98 per cent respectively, during the period 1992 to 2012 (EDGAR, 2019) (Figure 3).

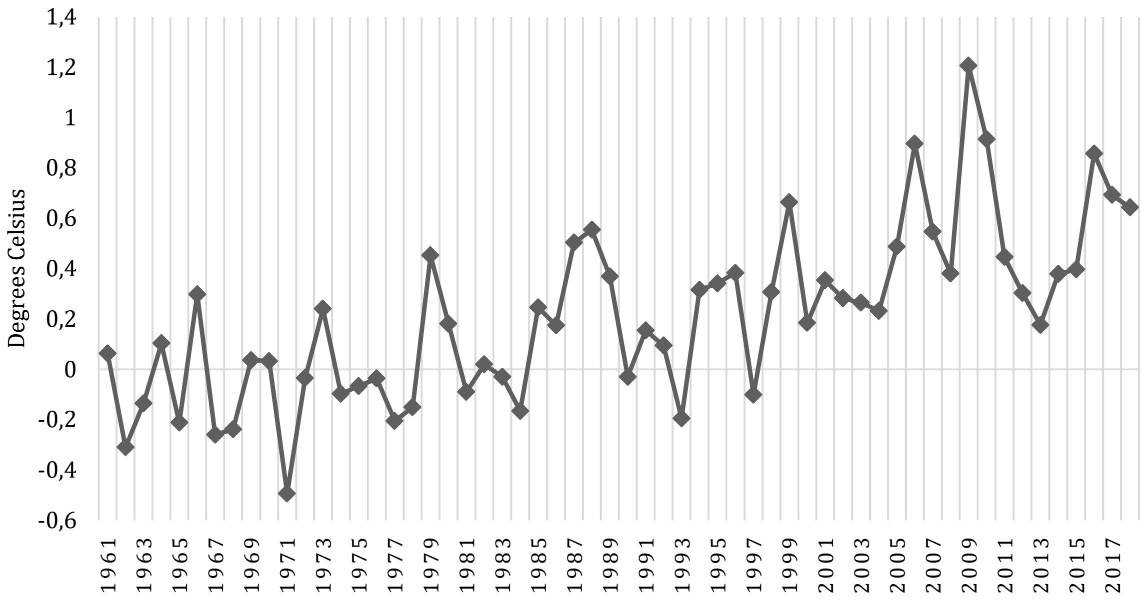
Figure 3: Growth rate of emissions (in per cent)



Source: Authors' illustration based on data from Emissions Database for Global Atmospheric Research (EDGAR) (EDGAR, 2019).

Global warming is wreaking havoc all over the world, and its impacts are being overtly felt in Bangladesh as well. Many countries of the world are witnessing a rise in annual average temperatures and records of temperature highs are being broken repeatedly. In Bangladesh, annual average temperatures increased by 0.64 per cent per year in 2018, which was 10.20 times faster than the annual average temperature increase of 0.06 per cent in 1961 (FAO, 2019) (Figure 4).

Figure 4: Annual average temperature change (in degrees Celsius)



Source: Authors' illustration based on data from FAOSTAT (FAO, 2019).

3. METHODOLOGY

At the very outset of the empirical analysis, missing values were encountered for several SDG indicators. This represented a problem, since forecasting a time series with limited number of observations and gaps in the data could lead to biased results. In order to resolve this issue, this study took advantage of the Expectation Maximisation (EM) algorithm to calculate estimated values of the missing data. The EM algorithm is an unsupervised machine learning algorithm which can be used for iteratively calculating maximum likelihood estimates from data which is missing at random (Dempster, Laird, & Rubin, 1977) (McLachlan & Krishnan, 2008). The EM algorithm is applicable for use with a wide variety of 'incomplete data' (Bishop, 2006), including data which is missing at random (Rubin, 1976). The term 'incomplete data' means that there are two sets of random variables, one of which is unobserved, while the other is observed (Alpaydin, 2010).

Suppose, there exist two sets of random variab7les $\mathcal{X}$ and $\mathcal{Y}$, where $\mathcal{X}$ is unobserved and $\mathcal{Y}$ is observed. Assume that there is a many-to-one mapping from $\mathcal{X}$ to $\mathcal{Y}$, such that the unobserved data x in set $\mathcal{X}$ are observed only indirectly through the observed data y in set $\mathcal{Y}$ (Moon, 1996). Then, the specification of the complete data, *f*, is linked to the specification of the incomplete data, g, through

$$g(y|\Phi) = \int_{\mathcal{X}(y)} f(x|\Phi)\,\mathrm{dx},$$

where, in the case of data missing at random, Φ is assumed to be independent of the parameters of the missing data process (Dempster, Laird, & Rubin, 1977). The EM algorithm aims to calculate a value of Φ which maximises $g(y|\Phi)$, the specification of the incomplete data, by utilising $\mathrm{f}(x|\Phi)$, the specification of the complete data (Dempster, Laird, & Rubin, 1977). The EM algorithm iterates between the expectation step, or E-step, and the maximisation step, or M-step, until convergence (Marsland, 2009). In the E-step, the expected values of the unobserved variables are calculated, and in the M-step, new values of the parameters that maximise the log likelihood of the data are found, given the expected values of the unobserved variables (Russell & Norvig, 2010). Following Dempster, Laird, & Rubin, 1977, assume that $\Phi^{(p)}$ denotes the current value of Φ after *p* cycles of the algorithm. Then the general form of the EM algorithm can be defined as:

$$Q(\Phi'|\Phi) = E(logfx|\Phi')|y, \Phi)$$

Now the EM iteration $\Phi^{(p)} \rightarrow \Phi^{(p+1)}$ can be defined as follows:

E-step: Calculate $Q\left(\Phi\middle|\Phi^{(p)}\right)$

M-step: Select $\Phi^{(p+1)}$ to be a value of $\Phi \in \Omega$ which maximises $Q\left(\Phi\middle|\Phi^{(p)}\right)$, where Ω is an *r*-dimensional convex region.

Each iteration of the EM algorithm increases the log likelihood (Hastie, Friedman, & Tibshirani, 2008) (Russell & Norvig, 2010) until convergence is reached where no further increase in the log likelihood is possible (Bishop, 2006). The EM algorithm has several advantages over other iterative algorithms, as outlined in McLachlan & Krishnan, 2008, which is why it was used in this study. Once the missing values in the data were estimated using the EM algorithm, the status of each SDG indicator was forecasted until 2030 using an autoregressive integrated moving average (ARIMA) model.

In forecasts using an ARIMA model, the dependent variable is forecasted using a linear combination of its own past values as well as past values of the error term (Makridakis, Wheelwright, & Hyndman, 1997) (Hyndman & Athanasopoulos, 2018). An ARIMA model constitutes of an autoregressive, or AR, component, a provision for differencing non-stationary time series, or I component, and a moving average, or MA, component. The AR component implies that the dependent variable is regressed on its own past values, the I component implies that differenced values of the dependent variable are used, and the MA component implies that the dependent variable is regressed on the past values of the error term. In the ARIMA (*p*, *d*, *q*) model, *p* denotes the order of the AR component, *d* denotes the degree of first differencing involved, and q denotes the order of the MA component (Makridakis, Wheelwright, & Hyndman, 1997). The general *p*th-order AR model can be defined as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t,$$

where, c is the constant term, ϕ_j is the *j*th autoregressive parameter, and e_t is the error term at time t (Makridakis, Wheelwright, & Hyndman, 1997). The general *q*th-order MA model can be defined as:

$$Y_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q},$$

where, c is the constant term, θ_j is the jth moving average parameter, and e_{t-q} is the error term at time $t - q$ $(\text{Makridakis, Wheelwright, \& Hyndman, 1997})$. Combining the AR and MA models gives the ARMA model:

$$Y_t = c + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

Adding the provision for differencing to the ARMA model gives the general form of the ARIMA model:

$$(Y_t - Y_{t-1})^d = c + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

where, d denotes the degree of first differencing (Makridakis, Wheelwright, & Hyndman, 1997).

In order to identify suitable values of p, d, and q for the ARIMA models, the Box-Jenkins approach (Box & Jenkins, 1970) (Box, Jenkins, & Reinsel, 1994) was used. The Box-Jenkins approach is essentially based on the principle of parsimony or the Occam's razor (Tornay, 1938) which advocates that the simplest explanation of phenomenon is the best. While increasing the number of parameters in the model may increase the goodness of fit, but it compromises the degrees of freedom available to estimate the variability of the parameters (Enders, 2015). The Box-Jenkins approach for ARIMA forecasting involves four broad phases: identification, estimation, diagnostic checking, and forecasting (Bhaumik, 2015).

The model identification phase is initiated by checking if the time series is stationary by running augmented Dickey Fuller (Dickey & Fuller, 1979) (Dickey & Fuller, 1981) and Phillips-Perron (Phillips & Perron, 1988) unit root tests. The augmented Dickey-Fuller unit root test constitutes of estimating one or more equations using ordinary least squares in order to obtain an estimated value for the coefficient of interest, γ, and the associated standard error. Comparison of the subsequent t-statistic with the corresponding value reported in the Dickey-Fuller results enables us to decide whether to reject or not to reject the null hypothesis of $\gamma = 0$. The unit root can be detected using the Dickey-Fuller statistic. If the model has no intercept or trend, then we use the τ statistic, if the model has an intercept then we use the τ_μ statistic, and if the model has both an intercept and a trend then we use the τ_τ statistic (Enders, 2015). The augmented Dickey-Fuller test uses the *p*th order autoregressive process defined as:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_i$$

where,

$$\gamma = -\left(1 - \sum_{i=1}^{p} a_i\right) \text{ and } \beta_i = -\sum_{i=1}^{p} a_j$$

The null hypothesis is that the variable contains a unit root. The alternative hypothesis is that the variable was generated by a stationary process. If $\gamma = 0$, then we cannot reject the null hypothesis that the variable has a unit root. The augmented Dickey-Fuller test assumes that the errors are uncorrelated with each other and have constant variance.

For robustness check, in addition to the augmented Dickey-Fuller unit root test, the Phillips-Perron unit root test was also conducted. The Phillips-Perron test is non-parametric unit root test that modifies the test statistics after estimation in order to consider the effect of autocorrelated errors. This procedure allows for drawing valid inferences from large samples without estimating additional parameters in the regression model (Banerjee, Dolado, Galbraith, & Hendry, 1993). The error term in the Phillips-Perron unit root test regression model does not follow a white-noise process.

The variables which were found to be non-stationary in the unit root tests were differenced. Thus, the order of first differencing, *d*, was determined. Next the autocorrelation function (ACF) and partial autocorrelation functions (PACF) were plotted to determine the orders of the autoregressive and moving average components, *p* and *q*, respectively. Following

Makridakis, Wheelwright, & Hyndman (1997), the autocorrelation coefficient, r_k, used for plotting the ACF is defined as:

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2},$$

and the PACF is plotted by calculating the partial autocorrelation coefficient $\alpha_k = b_k$ from the regression:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots + b_k Y_{t-k}.$$

The ACF shows the relationship between Y_t and lagged past values of Y_t. However, the problem with ACF is that two values of Y_t, such as Y_t and Y_{t-2} may appear to be correlated since they are both correlated with a third value of $Y_{t,}$ such as Y_{t-1}, which falls in between them (Hyndman & Athanasopoulos, 2018). In order to circumvent this issue, PACF shows the relationship between Y_t and past values of Y_t after removing the effect of lags $1,2,3, \dots, k-1$ (Hyndman & Athanasopoulos, 2018). An AR process of order *p* will exhibit an ACF which will die out rapidly with an exponential decay or damped sine-wave and a PACF which will have spikes up to lag *p* before dying out (Box, Jenkins, & Reinsel, 1994) (Bhaumik, 2015). An MA process of order *q* will exhibit an ACF which will have spikes up to lag *q* before dying out and a PACF which will die out rapidly with an exponential decay or damped sine-wave (Box, Jenkins, & Reinsel, 1994) (Bhaumik, 2015). A mixed AR and MA process is expected when neither the ACF nor the PACF exhibit any distinct cut-off patterns (Bhaumik, 2015). In addition to examining the ACF and PACF plots, portmanteau tests such as the Box-Pierce test (Box & Pierce, 1970) and Ljung-Box test (Ljung & Box, 1978) were also considered to help in deciding the appropriate values of *p* and *q*.

Once suitable values for *p*, *d*, and *q* have been determined, the ARIMA models are estimated using maximum likelihood estimation, the details of which can be found in several sources

(Box, Jenkins, & Reinsel, 1994) (Hamilton, 1994) (Abraham & Ledolter, 2005). The estimated ARIMA models were re-examined to check if they were identified properly. If $m = p + q + P + Q$ is the number of terms in the model, then the Akaike's Information Criterion (AIC) (Akaike, 1974) is defined as:

$$AIC = -2logL + 2m,$$

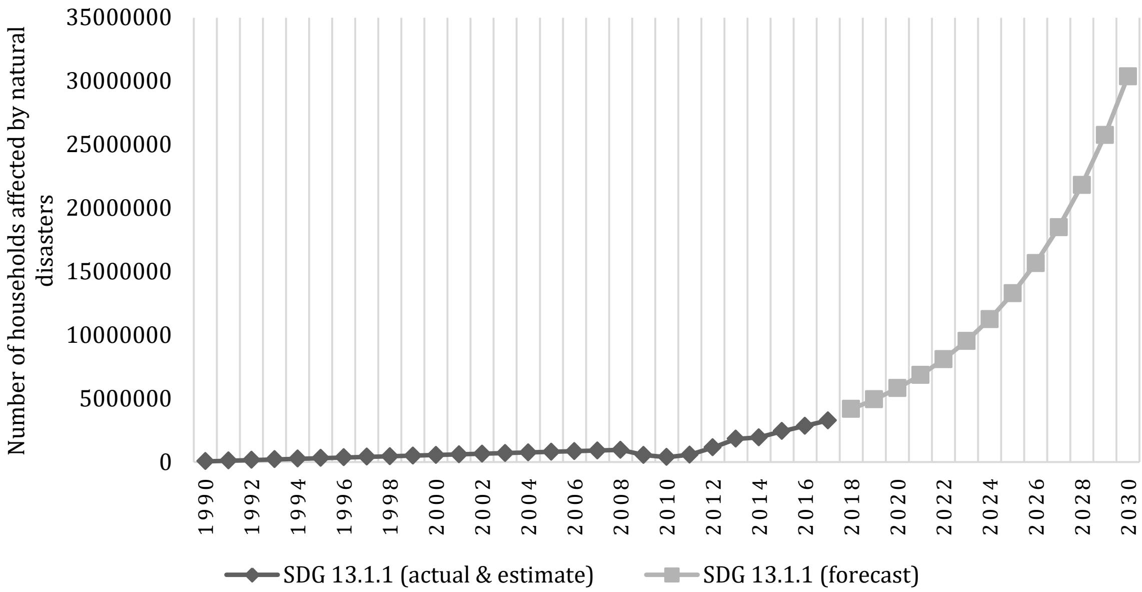
where, L denotes the likelihood (Makridakis, Wheelwright, & Hyndman, 1997). Among a group of competing ARIMA model specifications, the one which minimised the value of AIC was chosen. Following this, the residuals of the chosen model were examined with ACF and PACF plots and subjected to portmanteau tests, as recommended in the literature (Hyndman & Athanasopoulos, 2018).

The ARIMA model specifications derived using the Box-Jenkins approach were used as benchmark models for forecast averaging. Past research has pointed out the advantages of forecast averaging over the use of single forecasts (Clemen, 1989) (Makridakis & Hibon, 2000) (Timmermann, 2006), which is why the method was preferred for this analysis. The final forecasts were each based on the average of 100 different forecasts using smoothed AIC weights (IHS Global Inc., 2017).

4. FUTURE PROSPECTS

Although all natural disasters cannot be directly attributed to climate change, there is substantial evidence that anthropogenic climate change is responsible for the increase in the frequency, intensity and amount of heavy rainfall globally (Hoegh-Guldberg, et al., 2018). Hence, the increase in the number of households affected by natural disasters in Bangladesh over the years can be at least partly be explained by climate change. If the trend of increasing frequency and intensity of natural disasters continues, then 30,366,230 households in Bangladesh will be affected by natural disasters in 2030, which is 12.52 times higher than the number in 2015 (Figure 5).

Figure 5: Number of households affected by natural disasters (actual, estimate and forecast)



Source: Authors' calculations based on data from Bangladesh Bureau of Statistics (BBS) (BBS, 2015a)

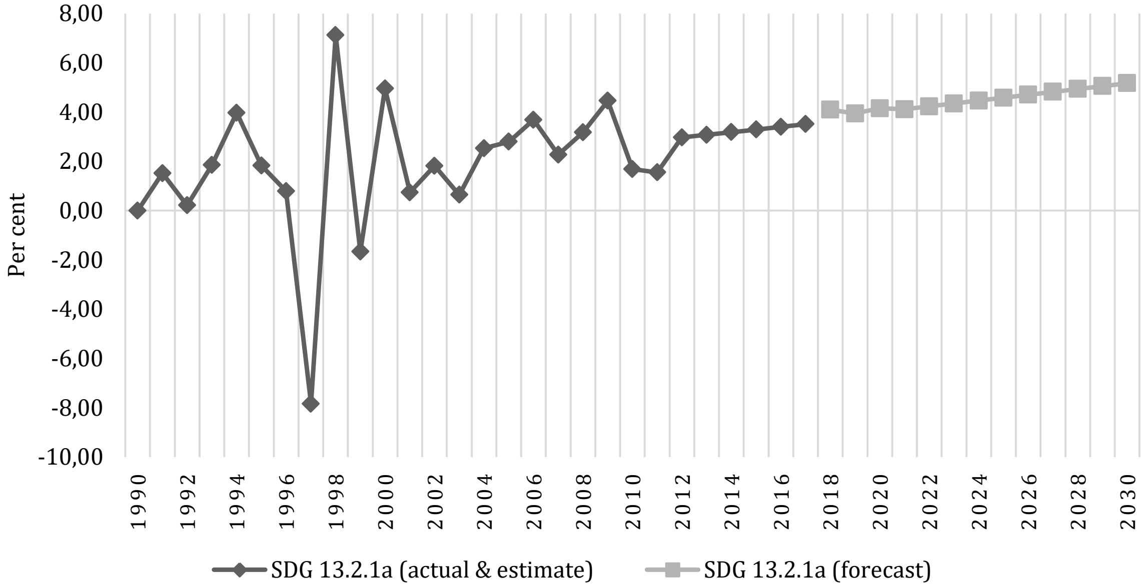
Note: (i) Missing values imputed with maximum likelihood estimates; (ii) Forecasts based on averaging of autoregressive integrated moving average (ARIMA) model forecasts; (iii) Household is defined as a group of people who share the same kitchen, including single persons

On the other hand, total greenhouse gas emissions increased by 1.81 per cent per year on average during the period 1992 to 2012 (EDGAR, 2019). If this increasing trend continues then in 2030 total greenhouse gas emissions in Bangladesh will increase by 5.17 per cent per year (Figure 6). Climate change is a global phenomenon for which Bangladesh alone is not responsible. Nonetheless, since Bangladesh is one the most vulnerable countries in the world to the adverse impacts of climate change, it is imperative for the country to leave no stone unturned in its efforts to mitigate the causes and adapt to the consequences of climate change.

Thus, steps must be taken to promote sustainable production and consumption practices, as well as to develop an environmentally-aware lifestyle.

Figure 6: Growth rate of total greenhouse gas emissions

(Actual, estimate and forecast)



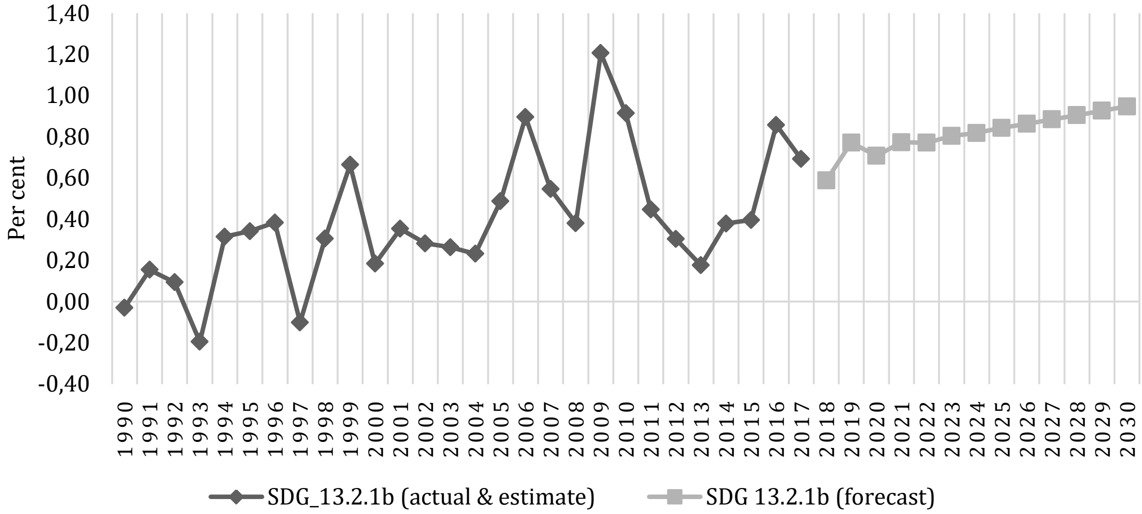
Source: Authors' calculations based on data from Emissions Database for Global Atmospheric Research (EDGAR) (EDGAR, 2019).

Note: (i) Missing values imputed with maximum likelihood estimates; (ii) Forecasts based on averaging of autoregressive integrated moving average (ARIMA) model forecasts.

If the disturbing trend of increase in annual average temperature continues, then by 2030 annual average temperature in Bangladesh will increase by 0.95 per cent each year (Figure 7). Such warming is bound to have effects adverse effects of agricultural productivity and human wellbeing while causing an increase in electricity consumption and frequency of severe cyclones.

Figure 7: Annual average temperature change (in per cent)

(Actual, estimate and forecast)



Source: Authors' calculations based on data from FAOSTAT (FAO, 2019).

Note: (i) Missing values imputed with maximum likelihood estimates; (ii) Forecasts based on averaging of autoregressive integrated moving average (ARIMA) model forecasts.

5. CONCLUSIONS

Bangladesh's high climate vulnerability is evident from the state of the indicators under goal 13. In recent years, the country has faced an increasing number of natural disasters — many of which are most likely induced by anthropogenic climate change. The total number of households affected by natural disasters has increased year by year, and if such trends continue then forecast suggests that more than 30 million households will be affected by climate-induced natural disasters in 2030. Climate-induced natural disasters have had substantial adverse impacts on individuals and communities, with high economic losses accompanied by large numbers of people suffering from sickness and injury, and children missing schooling days. The drivers of climate change show no signs of abatement, as greenhouse gas emissions keep rising. On the other hand, annual average temperatures are forecasted to keep increasing continuously till 2030, if the trends of the past persist.

6. RECOMMENDATIONS

Bangladesh has to tackle the impact of climate change in two broad ways: i) adaptive measures, and ii) mitigative measures. In case of adaptation, plans and policies undertaken by the government will have to be expedited and scaled up. This will require increased financial resources and state of the art technology. The Ministry of Environment, Forest and Climate Change will have to work closely with the Ministry of Finance for resource mobilisation. On the mitigation aspect, policymakers have to increase investment for reduction of greenhouse gas emissions in polluting sectors, including agriculture, manufacturing, transport, and construction sectors. However, since climate change is a global challenge, Bangladesh will have to work together along with the global community. Bangladesh will also have to demand for higher resources and technology transfer for tackling climate change related challenges more effectively.

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