Chapter 1
Introduction to Environmental Modelling

Many scholars have defined environmental modelling according to their disciplinary inclination. For example, DBW (2018) defines environmental modelling as "the application of multidisciplinary knowledge to explain, explore and predict the Earth's response to environmental change, both natural and human-induced". Wiki (2018) defined environmental modelling as "the creation and use of mathematical models of the environment. It is generally done either for pure research purposes, or inform decision making and policy". FES (2018) defined environmental modelling as the "modelling of natural processes associated with inanimate nature, such as hydrological and hydraulic modelling, modelling of chemical processes and processes in the atmosphere". Hauduc et al. (2015) defines environmental modelling as the process of accounting "for multiple variables and multiple objectives in systems with many processes occurring at different time scales". Delft3D (2018) define environmental modelling as the model that "is based on the transport of substances using the so-called advection-diffusion equation". FA (2018) defines environmental modeling as a model that "focus on only noise or emission outputs that presents a need to better consider noise, air quality, fuel burn, and greenhouse gas emissions interdependencies and their costs and benefits". EVO (2018) define environmental modelling as a model "that enable raw data to be transformed into useful information, through synthesis, simulation and prediction". Wiki (2018) defines environmental modelling as the "the process of using computer algorithms to predict the distribution of species in geographic space on the basis of a mathematical representation of their known distribution in environmental space".

In my own words, environmental modelling is building or developing efficient working systems (which may be in form of computational or mathematical or statistical or spatial application) to estimate, evaluate or mimic a real environmental situation with the aim to showing adequate understanding of the concept; manipulating or optimizing known parameters; and proffering sound solution(s) that can assist decision making process(es). There are different types of environmental models mentioned in literature. Figure 1.1 describes the pictorial concept of environmental modelling.

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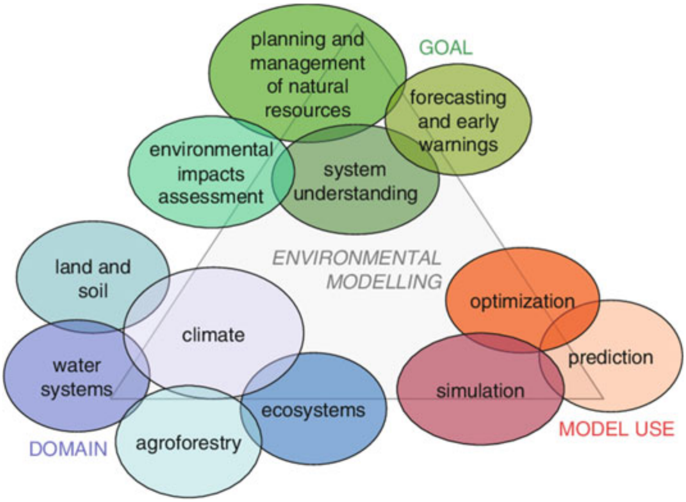

Fig. 1.1 Pictorial description of environmental modelling (Ogola 2007)

In the concept of Ogola (2007) as shown above, environmental modelling is divided into three subgroups, namely field application, known outcome and processing techniques. The 'field application' is made-up of water systems, land and soil, climate, ecosystems and agroforestry. In addition to the 'field application', there exist the renewable energy systems, geo-disciplines and atmospheric systems. Atmospheric systems are almost synonymous to the climate system, however, the distinction between these two systems is that atmospheric systems looks at the environmental forces that initiates wind systems, rainfall, surface temperature, snow cover etc. According to Ogola (2007), the 'known outcome' includes planning and management of natural resources, system understanding, forecasting and early warning, environmental impacts assessment. Lastly, the processing techniques include simulation, optimization and prediction. In addition to the concept of processing techniques is model development, model verification and model validation. A typical model development technique is presented by Logica (2018) in Fig. 1.2.

The quantitative environmental model has been described as a model that focuses on research, management and decision-making. The Integrated environmental model is the integration of multiple modeling techniques from different disciplines to solve environmental problems. Computational environmental model is the use of software applications for predictive or goal-oriented studies for specific environmental problems. Spatial environmental model describes an analytical process used to estimate or evaluate properties of spatial features that are gotten from geographical information system (GIS) or satellite imagery.

Researcher or modelers' routine in model formulation or application includes model calibration, validation, verification and sensitivity analysis. Model calibration is the process of assigning values to parameters, terms and constants. These values

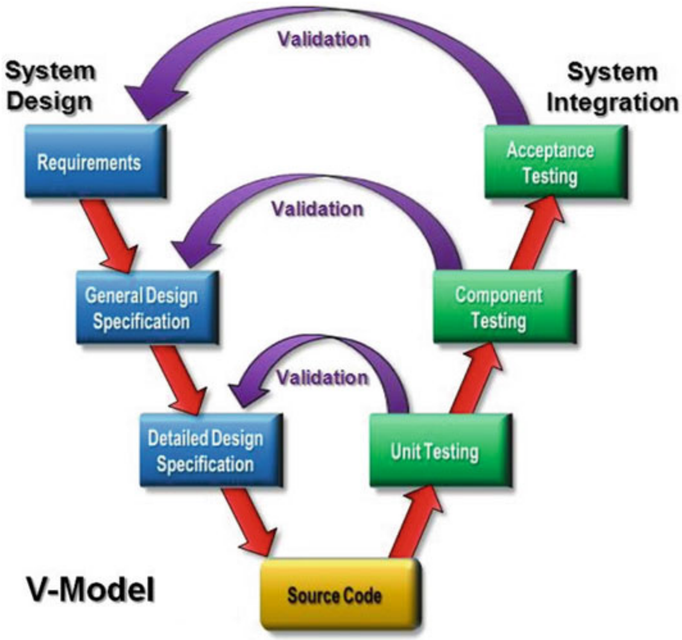

Fig. 1.2 Model development techniques (Logica 2018)

are used as input in the model to produce numerical output. Model validation is a process used for showing how the new model meets-up with some known standard. This standard may be the numerical output or behavioural trend of an existing work. Model verification is a process of proving that the modeling formalism is correct. This process includes debugging each compartment of the computer program; testing the mathematical models with live dataset; showing that the program logic is correct; comparing the sensitivity of the model with an existing model; re-scaling to detect errors or uncertainties in the model etc. Sensitivity analysis is a process which the modeler evaluates the responses of the model by considering changes in input parameters. Most time, the modeler or researcher develops standards to show that his/her model could assimilate dataset and comprehend every single detail or modification to the input parameters. In this chapter, the general outline on environmental models and few applications were discussed. Lastly, few aerosols model were considered.

1.1 General Outline of Environmental Models

In the general sense of environment model, its scope is quite bogus considering the multi-disciplinary interpretation of the word ‘environment’. In the field of economics, environmental model is referred to as ‘environmental-economic models’ that describes a qualitative or quantitative way of identifying least-cost policies or policy mixes of reducing environmental hazards. For example, Lanzi (2017) and OECD (2014) gave clear details on economic consequences of air pollution. Also, the economic consequences of climate model have been discussed by OECD (2015). In the field of psychology, environment model relates the behavior that emanates from changing environment and how that environment affects its inhabitants. Xiang et al. (2017) conducted a research on psychological and behavioral effects of air pollution, and how these effects are developed under different theoretical framework. It was argued that psychosomatic status was also responsible for adverse effect of air pollution.

From the above, it is quite interesting to note that environmental model is a multi-disciplinary affair and cannot be hinged mainly on fields of science and engineering. Environmental modelling can be divided into five broad types i.e. hydrology, climate, ecological, soil/geological and psychology/economy. The hydrological environmental models include surface water models, surface water runoffs model, subsurface water models and coastal models. From literature, surface water model can be represented mathematically in form of one and two dimensional models. The one-dimensional surface water models show a derivation that has multiple cross - sections perpendicular to the anticipated flow path (Zhang et al. 2013; Strong and Zundel 2014). Also, the one dimensional surface water model is characterized by the use of step-backwater methodology to determine water surface elevation and average flow velocity within each cross-section. The two dimensional surface water model considers the discretization of study location into grids; the determination of its water surface elevation within each grid element; and the estimation of flow into each adjacent grid element using finite difference method (Yoshioka et al. 2014). However, some researchers have adopted other methods for solving the two dimensional surface water model (Bai et al. 2016).

The difference between the one and two dimensional models can be summarized in the complexity of resolving parameters like flow time, grid elements, design configurations of the model, topography of the study area etc. Hence, the complexity of the surface water model does not depend on its features (i.e. one or two or three dimensional model) but on the researcher perception of the model design. The surface water runoffs model is a sub-division of the surface water model. Bhatt and Mall (2015) related the surface water runoffs to climate change in a simulation model. Like the surface water models, the subsurface water models are discussed with respect to its dimensions i.e. 1D, 2D or 3D. One of the famous subsurface water models is the Hydrus model. The Hydrus model has one (Hydrus-1D), two (Hydrus-2D) and three dimensional (Hydrus-3D) models. Hydrus 3D model theoretical frameworks is derived from the Richard's equation.

The coastal model relates the influence of the marine environment on terrestrial environment and vice versa. This concept is related to the sea-level rise. The dynamics of sea-level changes is crucial because it has great influence on the terrestrial environment. Church et al. (2001) propounded that human-induced global warming is a major cause of the global-mean sea-level rise that leads to an increase in the global volume of the ocean. Emetere and Akinyemi (2018) reported a computational environmental model that accurately evaluated the implication of climate change on the sea level changes in seven stations on the upper Atlantic.

The ecological environmental model is the second largest concept in environmental research. The sub-division of the ecological model cuts-across the specialized branches of ecology (Samiksha 2017) namely: habitat ecology, community ecology, population ecology, evolutionary ecology, taxonomic ecology, human ecology, applied ecology, ecosystem dynamics, ecological energetic, ecophysiology, genecology, paleoecology, ecogeography, pedology, ethology etc. For example, paleoecology is the study of the life of the past ages through the instrumentality of proven methods as palynology, paleontology, and radioactive dating. Seddon et al. (2013) summarized past paleoecology study and models in fifty salient perspectives.

The climate environmental model is adjudged the broadest research in environmental studies because it integrates broad topics—ocean, atmosphere, land surface, space, solar system etc. Among the specialized branches of climate model, the atmospheric researches have attracted more scientific publications in the past five decades. The quest to explain climate change and its numerous effects on the environment has increased research prospects in atmospheric studies or research. Also, atmospheric research is embedded in other specialized branches of climate modelling (Emetere 2014, 2016a, 2017a, b, c; Emetere et al. 2016; Emetere and Akinyemi 2017).

The soil/geological model is a compilation of all interactions below the soil that affects the terrestrial environment. For example, earthquakes, land-slides, earth tremor etc. are very vital in environmental modelling. Researchers have shown that models can be propounded to monitor, estimate and evaluate events below the earth surface (Gupta and Jangid 2011; Emetere 2017d). Also, some researchers have also modelled the effects of geological disturbances on the eco-system and atmosphere (Devine et al. 1984; Akinyemi et al. 2016).

There are many sub-modeling techniques in environmental modelling that help to understand certain phenomenon. For example, conventional modeling deals with the process of creating a simplified representation of reality to understand it and potentially predict and control its future development. Edward et al. (2009) used the conventional method to investigate carbon dioxide emission in trucks and vehicle. It was observed that typical van-based vehicle produced 181 g of carbon dioxide (CO_2), compared with 4274 g of CO_2 for an average trip by car and 1265 g of CO_2 for an average bus passenger. Jinduan and Dominic (2018) used the conventional modelling to investigate the short term water demand using daily water demand, daily maximum air temperature, and daily total rainfall data from Lexington, Ky., to develop and test several forecast models. Ghumman et al. (2011) used the conventional model to forecast rainfall run-off in the watershed in Pakistan. It was observed that conventional model maybe considered as an important alternative to conceptual models and it can be used when the range of collected dataset is short and of low standard.

Integrated modeling is a sub-modelling technique in environmental modelling and it refers to combination of a set of interdependent science-based components (models, data, and assessment methods) to form an appropriate modeling system. Hughes et al. (2011) used the integrated model to solve ground water problem in Thames.

The two models have been connected using the model linking standard OpenMI. The OpenMI (Open Modelling Interface) is an open IT standard that facilitates linking hydrological model with modules. The primary objectives of OpenMI platform are to develop, maintain and promote the use of multiple models. Johnston et al. (2011) used the integrated model to predict the state of freshwater ecosystem services within and across the Albemarle-Pamlico Watershed, North Carolina and Virginia (USA). The integrated model is made up of five environmental models that are linked within the Framework to provide multimedia simulation capabilities. The models are: the Soil Water Assessment Tool (that predicts watershed runoff); the Watershed Mercury Model (that simulates mercury runoff and loading to streams); the Water quality Analysis and Simulation Program (that predicts water quality within the stream channel); the Habitat Suitability Index model (that predicts physicochemical habitat quality for individual fish species); and the Bioaccumulation and Aquatic System Simulator (that predicts fish growth and production, as well as exposure and bioaccumulation of toxic substances).

Integrated assessment modeling is a sub-modeling technique in environmental modelling that considers an analytical approach to integrate knowledge from a variety of disciplinary sources to describe the cause-effect relationships by studying the relevant interactions and cross-linkages. Rotmans and van Asselt (2001) used the integrated assessment modelling to examine the history, general features, classes of models, strengths and weaknesses, and the dilemmas or challenges researcher encounter. However, there are uncertainties associated to the integrated model. This includes erroneous knowledge or data, inherent variability (Cullen and Frey 1999). Matott et al. (2009) reported that the total uncertainty of a given quantity may be characterized in one of four ways: purely irreducible (i.e. the quantity varies and the associated population has been completely sampled without error); partly reducible and partly irreducible (i.e. the quantity varies and the associated population has been partially sampled or sampled with error); purely reducible (i.e. the quantity does not vary but has been sampled with error); and certain (i.e. the quantity does not vary and has been sampled without error).

Probabilistic model (statistical or stochastic models) is referred as a sub- modelling technique that utilize the entire range of input data to develop a probability distribution of model output rather than a single point value. Sun et al. (2014) used the probabilistic model to predict the flow of four engineered nanomaterials (nano-TiO_2, nano-ZnO, nano-Ag and CNT) to the environment and to quantify their amounts in (temporary) sinks such as the in-use stock and (“final”) environmental sinks such as soil and sediment.

The model life-cycle is defined as one of the key concepts of systems engineering that generally consists of a series of stages regulated by a set of management decisions to estimate the maturity of the system to transcend from one stage to another. A pictorial definition of model life-cycle is shown in Fig. 1.3.

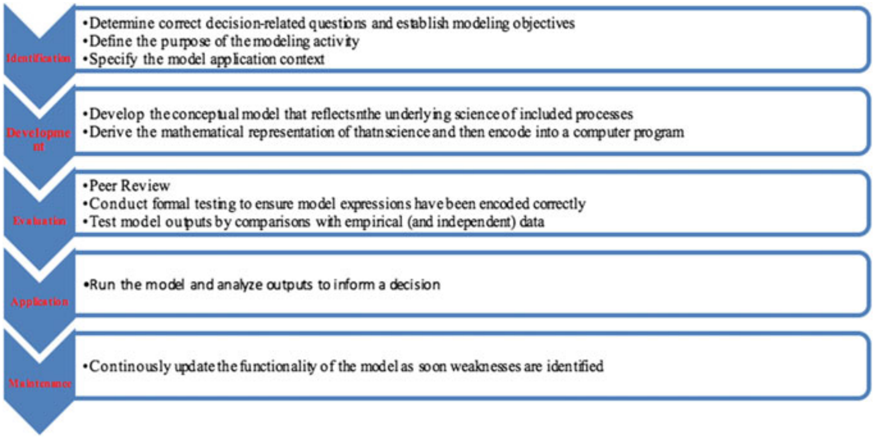

Fig. 1.3 Pictorial overview of model life-cycle

1.2 Dimensions of Environmental Models

Hämäläinen (2015) introduced the concept of behavioural issues in environmental modelling. This includes the salient issues that prompts a modeler or researcher to make decision on: the choice of method for his/her model; the choice of model to examine; the choice of approach in solving problems; the choice of whom to cite; the choice of whom to critic; the choice of research modalities; the mode of explaining model; the choice of whom to collaborate with. As much as it is good to conceive a model, it is essentially paramount for researcher to consider how to develop a model, test-run a model, validate a model, and expand model application. It is also good to understand the reality of the risk of making choices in environmental modeling. For example, Montibeller and von Winterfeldt (2015) highlighted a list of cognitive and motivational biases in decision making. Cognitive biases are systematic patterns of deviating from norm or rationality in judgment. This includes anchoring certain bias, equalizing bias, gain-loss bias, myopic problem representation, splitting biases, proxy bias, range insensitive bias and scaling. According to Hämäläinen (2015), the main goal of considering behavioral issues in environmental modelling is to improve the understanding of decision processes and to produce better outcomes (like predictions, decisions and policies) to avoid 'Hammer and Nail' syndrome in upcoming modelers. 'Hammer and Nail' syndrome is when a modeler or researcher uses only a single modelling tool to solve all kinds of problem. This challenge may emanate from some scientists who are clamoring for expertise in the use of a single tool. This kind of cognitive bias is called anchoring. In environmental modelling, veracity in understanding many tools is very important as it gives the modeler new perspectives to attain high level accuracy.

Generally, in scientific discuss, the 'Bandwagon effect' bias is very common. This kind of cognitive bias is sometimes referred to 'herds thinking' where there is the tendency to do (or believe) things because many other people do (or believe) the same. The recent trends in environmental modelling are worrisome because 'Bandwagon effect' is massively crumbling the possibility of creating new perspectives in a given field. Some 'old school' researchers (i.e. those who believe strictly on a concept) are forcibly rejecting opposing scientific hypothesis that seem to negate their believes on the validity of certain scientific postulations. This challenge leads to the question—is there a perfect model? Sterman (2002) answer to the question clearly shows that there is no perfect model, however, the usefulness of a model is a function of its perceived relevance.

Another common type of bias environmental researcher face is the 'Bias blind spot'. Victims of this kind of bias see their self as less biased than other people. This challenge has created wide disparity amongst scientists as it has played down on superior facts and upheld superior complexes. The beauty of knowledge is that we all cannot see from the same vintage point. While some observer can effortlessly explain their own side of a matter (may be due to less complexity of the observables), other observer may have difficulty to comprehend the complexities of observables. Some literatures in environmental studies are offensive because the writer castigates so many research works without a substantial evidence to support their claims.

The 'Continued influence effect' is a known cognitive bias in environmental modelling that creates a virtuous cycle for a long period of time. This type of bias occurs when there is the tendency to believe previously learned misinformation even after it has been corrected. A typical example is the application or functionality of the general circulation models (GCMs). Wilby et al. (2002) argued that GCMs are restricted in their usefulness for local impact studies by their coarse spatial resolution (typically of the order 50,000 km^2) and unable to resolve important sub-grid scale features such as clouds and topography. However, Min-Seop and In-Sik (2018) has successfully resolved the sub-grid scale challenge by considering a three-dimensional cloud resolving model simulation to estimate the appropriate ratios of the sub-grid scale vertical transport to the total vertical transport of moist static energy for different horizontal resolutions in the cumulus base mass flux. The identification of an error in an existing model and the perceived solution to the problem are very important in environmental modelling. Hence, beginners in environmental modelling should consciously avoid this pit-fall because it would make the modeler or researcher exhaust much energy to accomplish any meaningful task.

The opposite of the 'Continued influence effect' bias is the 'Irrational escalation'. This bias occurs when people justify increased investment in a decision, based on the cumulative prior investment, despite new evidence suggesting that the decision was probably wrong. This kind of bias is common where there is the 'herds thinking'. Unfortunately, research institutions are more culpable to exhibit this type of bias. Many upcoming modeler sometimes face the challenge to have this bias based on their perception of the name of the research institute.

Most upcoming modeler have the 'Ostrich effect' bias. This bias entails the victim tendency to ignore obvious (negative) facts in the formulation or modification of a model. The antidote to this bias is consulting many literatures before conceiving the parametric concept of the model.

As discussed earlier, the ultimate objective of an environmental model is its relevance or applicability for policy making, software development etc. In recent research work, modeler or researcher are expected to show the application of their model, its reproducibility, relevance, accuracy etc. Some modeler may go an extra mile in expanding the scope of their environmental model to other branches of environmental studies. For example, the thermographic model has been proven to show great success in interpreting meteorological imbalances (Emetere 2014). This effect was applied to explain the thermal distribution during volcanic eruption (Emetere 2017d). Lastly, the knowledge that was gain from the thermal properties sub-surface elements led to the extensive use of the model to detect hydrocarbon entrapment in the earth surface (Emetere et al. 2017a).

The advance stage of model application is the adoption of the model in regulatory development such as setting standards, or enforce regulatory requirements. For example, the Environment Protection Agency (EPA) has adopted AERMOD application software for setting standards for air pollution dispersion from point sources. AERMOD modeling system includes extensive documentation, model code, user's guide, supporting documents, and evaluating databases, all of which are available on the web site of the EPA Support Center for Regulatory Atmospheric Modeling (NRC 2007).

In like manner, SUTRA (saturated–unsaturated transport) and SUTRA^{-1} models are used as standards for evaluating the accuracy of hydrologic and hydrogeochemical processes i.e. movements of pollutants and water (Bobba et al. 2000). SUTRA was developed in 1984 by United States Geological Survey (USGS). It is a three-dimensional groundwater model that simulates solute transport (i.e. salt water) or temperature in a subsurface environment.

The selection of models as standards sometime may not be hinged on only its accuracy. Sometimes, the selection of models is often based on familiarity. Hence, the criteria for universal acceptance of any model may be the versatility of the inventor or modeler to arose wider usage of the model. This may be the reason why institutional based models are promoted than individual models.

1.3 Aerosol Models

The main focus of this book is to discuss the dynamics of environmental modelling with emphasis on re-processing of satellite imageries of atmospheric aerosol distribution. The definition and sub-division of atmospheric aerosol model is still unclear because its concept is very broad—considering the factors that triggers its distribution, dispersion and particulate life-time. Hence, authors define the types of aerosol models according to their research objectives. For example, Shettle and Fenn (1979) listed the types of aerosols model as rural aerosol model, urban aerosol model, maritime aerosol model, tropospheric aerosol model and fog model. In this section, aerosol models will be discussed based on its basic properties.

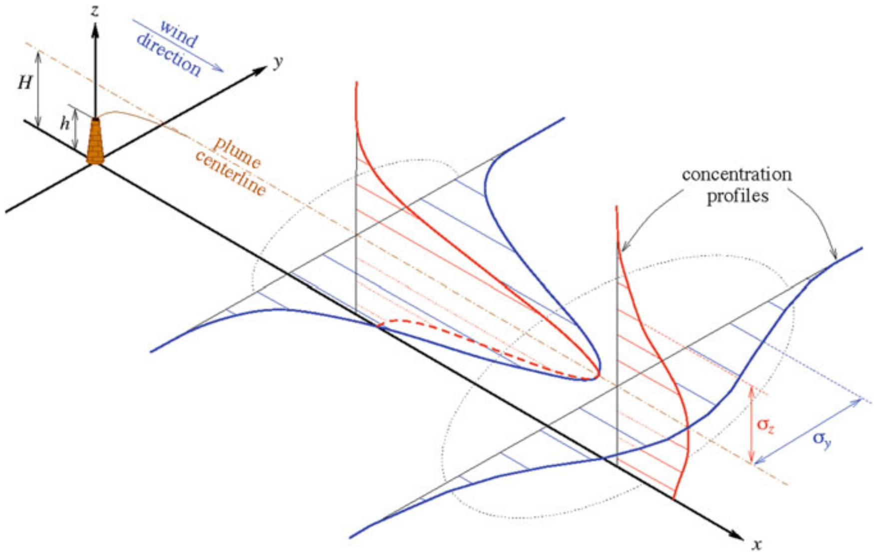

Fig. 1.4 Basics of advection-dispersion models (Stockie 2011)

1.3.1 Advection-Dispersion Models

Advection-dispersion models are mostly developed on regional scale. This is because regional meteorology differs from one geographical location to another. The basics of advection-dispersion models is shown in Fig. 1.4. Till date, it is still a huge task—integrating regional models into a complex global scale. One of the reason is that most regional advection-dispersion models are contested based on its theoretical soundness and computational validity. Zhang et al. (2014) investigated the global atmospheric aerosol transport model using 3D advection-diffusion equations that was an extension of the 2D advection-diffusion equation:

$$\frac{\partial c}{\partial t}+u_x\frac{\partial c}{\partial x}+u_y\frac{\partial c}{\partial y}+u_z\frac{\partial c}{\partial z}=k_x\frac{\partial^2 c}{\partial x^2}+k_y\frac{\partial^2 c}{\partial y^2}+k_z\frac{\partial^2 c}{\partial z^2}+\lambda c \tag{1.1}$$

where c is contaminant concentration; t is time; u_x, u_y, u_z represent wind speed in the three directions x, y, z respectively; k_x, k_y, k_z represent turbulent diffusivity in three directions; λ is the climatic factor, which can be its emission source, chemical conversion, dry deposition and wet scavenging.

The Euler finite difference method for numerical simulation which has a horizontal resolution $4^\circ \times 5^\circ$ and a vertical direction (divided into 11 sub-layers) was used to resolve Eq. (1.1). The model was queried because the application of the model was based on laboratory framework only.

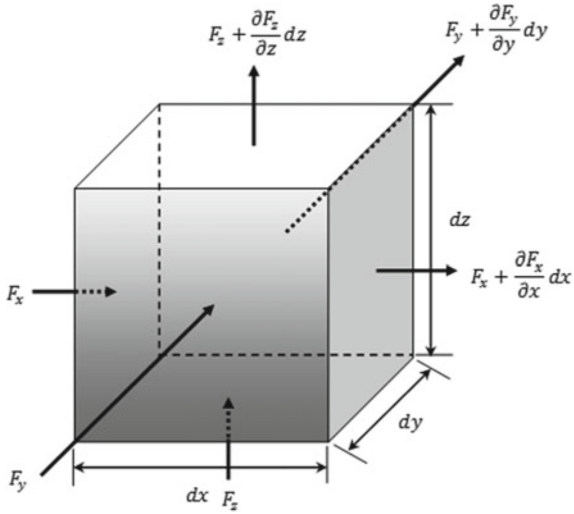

Fig. 1.5 Basics of box models (Guwahati 2014)

Holmes and Morawska (2006) developed dispersion model whose principles was based on the box model (BM). The BM operates on the principle of conservation of mass. The box model is familiar in atmospheric research. Choo-in (2001) applied the box model to estimate the pollutants in a street tunnel in Thailand. The box model works perfectly when the air mass is well mixed and concentrations are uniform throughout. When the box is not defined, pollutants are formed within the box only; hence, the information on the local concentrations of the pollutants is considered as negligible. The basics of the box-model is shown in Fig. 1.5.

The Gaussian model (GM) is the most popular model used in atmospheric dispersion modeling. Gaussian or plume models operate based on the Gaussian distribution of the 2D or 3D concentration of the plume under steady state conditions. The Gaussian distribution of the plume is under certain influences like turbulent reflection from the surface of the earth, dimension of transport, boundary layer (especially when the mixing height is low), stability classes or travel time from plume sources.

Ahmada (2011) worked on the dispersion of atmospheric pollutants using two dimensional advection diffusion equations. He started with the generalized advection-diffusion equation given below

$$\frac{\partial C}{\partial t} = \mu \frac{\partial^2 C}{\partial x^2} - u \frac{\partial C}{\partial x} \tag{1.2}$$

and obtained the two-dimensional advection-diffusion equation given as

$$\frac{\partial C}{\partial t} - \mu \left(\frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2} \right) + u \frac{\partial C}{\partial x} + v \frac{\partial C}{\partial y} + \varpi C = \frac{f}{H} \tag{1.3}$$

where C is the concentration of pollutants, H is the depth occupied by pollutants, u is the wind velocity or drift velocity, f is the power of the source, ϖ is the pollutant chemical activity coefficient of pollutants and μ is the horizontal diffusion coefficients. The boundary conditions used were the zero Dirichlet boundary condition, Neumann boundary condition and periodic boundary condition. The finite difference approach was adopted in order to obtain the numerical solutions of Eq. (1.3). The solutions for first order forward difference, first order backward difference, first order central difference, second order central difference, central differences for two dimensional functions of the Crank-Nicolson method were determined. The model propounded has three external parameters, namely the pollutant diffusion coefficient μ, the drift velocity of air u and the pollutant chemical activity coefficient ϖ.

Thongmoon et al. (2007) worked on the numerical solution of a 3D advection-dispersion model for pollutant transport-using the forward in time and centre in space (FTCS) finite difference method. The paper is an extension of the Choo-in (2001) box model with a different dimensionality.

$$\frac{\partial C}{\partial t} + u\frac{\partial C}{\partial x} + v\frac{\partial C}{\partial y} = D_h\frac{\partial^2 C}{\partial x^2} + D_h\frac{\partial^2 C}{\partial y^2} + D_v\frac{\partial^2 C}{\partial z^2} \tag{1.4}$$

where u and v are constant wind speeds in the x and y-directions respectively. D_h and D_v are constant dispersion coefficients in the x and z-directions respectively.

Benson et al. (2000) worked on the application of a fractional advection-dispersion equation (FADE). They used fractional derivatives to study the scaling behavior of plumes that undergo Levy motion. This scaling behavior is in time and space of the heavy tailed motion (Daitche and Tamas 2014). However, the second-order dispersion arises for a thin tailed motion. Under this condition, very large motions are completely ruled out. Contrary to the thin tailed motion, the fractional advection-dispersion equation considers a very large transition of particles which arise from high heterogeneity (Benson et al. 2000). The FADE is effective (when the scaled α-stable density is known) to predict distances of particles in closed forms and their concentrations versus time. FADE have been found to be accurate in a laboratory settings. However, its accuracy under geographical uncertainties has not been resolved.

1.3.2 Aerosol Optical Depth: Satellite Retrieval Model

The AOD is a vital parameter that applies to determining air quality that affects: environment and life-forms; monitoring volcanic and biomass pollution; forecasting and now-casting earth radiation budget and climate change; estimating variability of aerosols and its size distribution in the atmosphere. The greater the magnitude of the AOD at specified wavelengths, the lesser the chances of light at that wavelength to reach the Earth's surface. Aerosol optical depth is the measurement of transparency of the atmosphere. When AOD is less than 0.1 and 1.0, it indicates a crystal clear sky and very hazy conditions, respectively. AOD measures the amount of light lost due to the presence of aerosols or aerosols distributed on a vertical path through the atmosphere.

The sun photometer measures the AOD using the Beer-Lambert-Bouguer law where the voltage (V) is directly proportional to the spectral irradiance (I) measured by the sun photometer. The mathematical expression for the Beer-Lambert-Bouguer law (Faccani et al. 2009; He et al. 2012) is given:

$$V(\lambda) = V_o(\lambda)d^2\exp(-\tau(\lambda)_{tot} \times m) \tag{1.5}$$

where $\tau(\lambda)_{tot}$ is the total optical depth, and m is the optical air mass, V_o is the extraterrestrial voltage, V is the digital voltage measured at wavelength λ, d is the ratio of the average to the actual Earth-Sun distance. The Beer-Lambert-Bouguer equation (He et al. 2012) could also be modified as

$$\tau_a = \frac{\left(In\left(\frac{V_o}{R^3}\right) - In(V - V_{dark}) - a_R\left(\frac{p}{p_o}\right)m\right)}{md} \tag{1.6}$$

where τ_a is the aerosol optical depth, V_o is the calibration constant for the sun photometer, R is the Earth-Sun distance, d is the day of the year, V and V_{dark} are the sunlight and dark voltages from the sun photometer respectively, a_R is the contribution of optical thickness of molecular (Rayleigh) scattering of light in the atmosphere, p is the station pressure, p_o is standard sea level atmospheric pressure, m is the relative air mass and written as $m = \frac{1}{\sin(\theta)}$, θ is the solar elevation angle.

The measurement of AOD is complex because aerosol is not solely responsible for the scattering or absorption of light. Other atmospheric constituents, for example, methane, ozone, nitrogen oxides, carbon (IV) oxide, water vapour scatter or absorb light, hence their joint AOD can be calculated as shown mathematically below (Liu et al. 2011):

$$\begin{aligned}\tau(\lambda)_{aerosol} = \tau(\lambda)_{tot} - \tau(\lambda)_{water} - \tau(\lambda)_{Rayleigh} - \tau(\lambda)_{O_3} \\ - \tau(\lambda)_{NO_2} - \tau(\lambda)_{CO_2} - \tau(\lambda)_{CH4}\end{aligned} \tag{1.7}$$

where $\tau(\lambda)_{Rayleigh}$ is the optical depth of the Rayleigh scattering. Spectral aerosol optical depths at wavelength 440–870 nm are typically used to estimate the size distribution of aerosols. The size distributions of aerosols are better described by the Angstrom parameter (α) which can be calculated using two or more wavelengths. The most popular mathematical representation (Liu et al. 2011) of α is given as

$$\alpha = -\frac{d\ In\,\tau_a}{d\ In\,\lambda} \tag{1.8}$$

where τ_a is the aerosol optical depth, α is the Angstrom parameter and λ is the wavelength. When α is equal or greater than 2, a fine mode aerosol is dominant. When α is near zero, the coarse mode aerosol is dominant.

AOD can be measured using either ground (sun photometer) or remotely sensed techniques. AERONET is known for harnessing ground measurements. It gives quality data on all aerosol column properties. However, it has a major limitation of few sites in developing and under-developed regions. The principle of remotely sensed technique is based on the ability of satellite to capture particulates in the atmosphere through the reflection and absorption of visible and infrared light. Remote sensing technique is available on some sites. For example, Aura/OMI are used to obtain aerosol optical depth at ground pixel resolution of 0.25° latitude/longitude grid and 1° latitude/longitude grid resolution; Meteor-3, TOMS and NIMBUS 7 are used to obtain aerosol optical depth at ground pixel resolution of $1° \times 1.25°$ latitude/longitude grid resolution. Other satellite sites for obtaining AOD are Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS), Polarization and Directionality of the Earth's Reflectances (POLDER) over ocean and Multi-angle Imaging SpectroRadiometer (MISR), Advanced Along Track Scanning Radiometer (AATSR), Total Ozone Mapping Spectrometer (TOMS), Ozone Monitoring Instrument (OMI), MODIS, Atmospheric Infrared Sounder (AIRS), TIROS Operational Vertical Sounder (TOVS) over land (NOAA 2015).

The main importance of the AOD is to determine the aerosol size distribution. In this study, the aerosol size distribution was obtained using the Multi-angle Imaging SpectroRadiometer (MISR). The MISR was launched in 1999 to measure the intensity of solar radiation reflected by the planetary surface and atmosphere. It operates at various directions, that is, nine different angles (70.5°, 60°, 45.6°, 26.1°, 0°, 26.1°, 45.6°, 60°, 20.5°) and gathers data in four different spectral bands (blue, green, red, and near-infrared) of the solar spectrum. The blue band is at wavelength 443 nm, the green band is at wavelength 555 nm, the red band wavelength 670 nm and the infrared band is at wavelength 865 nm. MISR acquire images at two different levels of spatial resolution; local and global mode. It gathers data at the local mode at 275 m pixel size and 1.1 km at the global mode. Typically, the blue band is to analyse coastal and aerosol studies. Blue band is higher at regions of increasing vegetation. The scope of the blue band may include ice, snow, soil or water. The blue band can therefore be divided into continental model blue band, desert model blue band, urban model blue band, biomass burning model blue band. The green band is to analyse Bathymetric mapping and estimating peak vegetation. The red band analyses the variable vegetation slopes and the infrared band analyses the biomass content and shorelines.

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