Tropical cyclone track forecasting techniques: A review

Chandan Roy and Rita Kovordanyi

Linköping University Post Print

N.B.: When citing this work, cite the original article.

Original Publication:

Chandan Roy and Rita Kovordanyi, Tropical cyclone track forecasting techniques: A review, 2012, Atmospheric research, (104-105), 40-69.

<http://dx.doi.org/10.1016/j.atmosres.2011.09.012>

Copyright: Elsevier

<http://www.elsevier.com/>

Postprint available at: Linköping University Electronic Press

<http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-74115>

Tropical Cyclone Track Forecasting Techniques—A Review

Chandan Roy, Rita Kovordányi

chandan.roy@liu.se, rita.kovordanyi@liu.se

Dept. of Computer and Information Science

Tel. +46 13 282784

Fax: +46 13 221431

Linköping University, SE-581 83 Linköping, Sweden

Tropical Cyclone Track Forecasting Techniques—A Review

Abstract

Delivering accurate cyclone forecasts in time is of key importance when it comes to saving human lives and reducing economic loss. Difficulties arise because the geographical and climatological characteristics of the various cyclone formation basins are not similar, which entails that a single forecasting technique cannot yield reliable performance in all ocean basins. For this reason, global forecasting techniques need to be applied together with basin-specific techniques to increase the forecast accuracy. As cyclone track is governed by a range of factors variations in weather conditions, wind pressure, sea surface temperature, air temperature, ocean currents, and the earth's rotational force—the coriolis force, it is a formidable task to combine these parameters and produce reliable and accurate forecasts. In recent years, the availability of suitable data has increased and more advanced forecasting techniques have been developed, in addition to old techniques having been modified. In particular, artificial neural network based techniques are now being considered at meteorological offices. This new technique uses freely available satellite images as input, can be run on standard PCs, and can produce forecasts with good accuracy. For these reasons, artificial neural network based techniques seem especially suited for developing countries which have limited capacity to forecast cyclones and where human casualties are the highest.

Key words: cyclone track forecasting, cyclone forecasting techniques, cyclone forecasting models, artificial neural networks, hurricane, typhoon

1 Introduction

A tropical cyclone is a low-pressure system with a warm core that forms over tropical and subtropical waters. The tropical and subtropical oceans receive large amounts of energy from the sun. This energy is released into the atmosphere in the form of water vapor. The release of heat causes an upward motion of air, creating a low-pressure zone that is set into spin by the rotation of the earth. When the energy contained in this spiraling airflow is high enough, a cyclone is formed. Although low-pressure zones form frequently over the tropical oceans, only a fraction of them reach the intensity of a tropical cyclone (Anthes, 1982). Zehr (1992) suggests that tropical cyclones are formed in two successive stages:

1. Stage 1: A mesoscale vortex is produced by mesoscale convective complexes (which can be regarded as a large scale thunderstorm system with a horizontal extension of approximately 100 to 200 km)
2. Stage 2: The mesoscale vortex is intensified through a decrease of central pressure and an increase of the spiraling wind flow until a cyclone is formed.

Though the development of tropical cyclones follows these two consecutive stages, the initial formation of low-pressure zones and the development of these low-pressure zones into cyclones could potentially be affected by several factors (Chan and Kepert, 2010; Gray, 1968, 1979, 1998):

1. Heat accumulated in the ocean waters comprises the main source of energy for developing cyclones. This means that the ocean water must be warm enough ($\geq 26.5^{\circ}\text{C}$)

up to a certain depth (usually 50 m) so that the heat build-up can supply the energy necessary for the formation of the cyclone.

2. A situation must prevail where atmospheric temperature decreases sharply with height (like in a thunderstorm). The differences in temperature facilitates heat transfer from the warm ocean surface into the atmosphere.
3. Mid-tropospheric air layer must be moist as it promotes large scale thunderstorm activity.
4. The low pressure zone must *not* be located too close to the equator (it must be at least at a 500 km distance from the equator so that the low pressure system can be sustained through the coriolis force).
5. The low pressure zone must have sufficient vorticity¹ and inflow of air (convergence).
6. Wind speed must not vary too much with height (variation should be less than 40 km/h between the ocean surface and the troposphere). If the magnitude of wind change with height is more than 40km/h then the formation of cyclone is disrupted or if a cyclone is already formed then it weakens or destroy the tropical cyclone.

These factors are not fully independent and some of them apply are present over tropical waters during a large part of the year (e.g., factors 1 and 2 are normally present over the tropical oceans during the summer months). Even if the above mentioned conditions are necessary for the formation and development of cyclones, cyclones do not always form in the presence of these conditions. Since cyclones do not form at particular locations over tropical oceans, factors that cause an individual storm to form varies in nature and degree compared to the general factors listed above (Chan and Kepert, 2010). Also there is a temporal aspect: Whether or not a depression continues to develop into a cyclone is dependent on the surrounding environment's ability to sustain favorable conditions long enough for the cyclone to be formed (DeMaria et al. 2001; Emanuel, 2007; Gray, 1998).

The tropical atmosphere is characterized by travelling mesoscale wind packages which oscillate in and out of balance with their surrounding pressure fields. These travelling wind fields are capable of producing temporary zones of strong wind convergence and divergence. Such wind fields are frequently visible in the tropical region in the form on short-lived tropical convective systems such as cloud clusters or mesoscale convective systems. These mesoscale convections are the basic requirement for cyclone formation (Gray, 1998). Winds moving upward from lower atmospheric levels—usually upward moving air within a low pressure system—are sometimes able to penetrate to near the center of a cloud cluster then the conditions are favorable for the formation of tropical cyclones. If the winds are not present or fail to penetrate the cloud cluster a cyclone is less likely to develop, even though all other necessary conditions are present (Fitzpatrick, 2006; Gray, 1998).

After its initial formation, a cyclone usually moves over the oceans, in a direction away from the equator, for a few days to finally decay over the ocean or cross a coastline and decay over land. The typical lifetime of a tropical cyclone is 3-5 days but can sometimes last for 2-3 weeks if the cyclone remains over sea (Debsarma, 2001). During its lifetime, the cyclone can travel hundreds of kilometers, what is known as the cyclone's track. Cyclones that maintain a

¹ Vorticity in this context is a measure of the amount of rotation of air.

continuous direction during their lifetime are known as non-recurving. In contrast, recurving cyclones change their path one or several times during their lifetime.

As cyclones are formed, move and sometimes decay over sea, they cannot be properly monitored from land. Since the beginning of the 1960s, when the first weather satellite TIROS-1 was launched, satellite images have become one of the major data sources for cyclone monitoring and forecasting.

Forecasting of cyclones involves the prediction of several interrelated features, such as the cyclone's track, intensity, induced storm surges and accompanying rainfall, and the coastal areas threatened (Holland, 2009). Among all these interrelated features it is most important to know in which direction a cyclone will move so that the inhabitants of potentially affected areas can be warned well ahead of time, in this way minimizing damage to life and property. For this reason, forecasting of cyclone track has been considered as one of the most important forecasting functions by many meteorological offices around the world (McBride and Holland, 1987). As cyclones formed in different basins exhibit large variation in behavior, meteorological offices tend to use a combination of techniques to forecast cyclones in order to achieve highest possible accuracy and reliability.

All forecasting techniques have in common that they take into account the recent-past behavior of the current cyclone and/or the behavior of previously encountered, similar cyclones. Previous cyclones can be similar to the present one in terms of their creation—created in the same ocean basin and/or during the same season or even the same month during a previous year. They can also be similar in terms of their behavior pattern—they may have had a similar movement track as the present cyclone has exhibited up till present time. The basic assumption is that whatever forces are affecting the present cyclone also have affected these previous cyclones, also called *predictors*, and that studying these predictors will therefore help to forecast the track of the current cyclone. Various cyclone track forecasting techniques differ, however, in how the past data are selected and how the data are utilized. Currently employed cyclone track forecasting techniques can be based on (Hope and Neumann, 1977; Neumann and Pelissier, 1981):

1. Averaging across previous cyclones
2. Statistical modeling of previous cyclones
3. Numerical and dynamical modeling of general meteorological and physical forces affecting cyclones
4. Other ways of considering past data, for example, detection of reoccurring patterns by human experts

In this paper we briefly describe the currently used cyclone track forecasting methods. In practice, these methods often involve a combination of techniques. We have therefore chosen to group the various methods according to the main technique employed (Figure 1). Within the groups, we have maintained a chronological order, so that methods that have been in use for longer are presented first. When describing different groups of techniques we have tried to focus on *the data necessary to run the model* (predictors), *complexity of the model and computational resources required to run the model* (which calculations or equations are used and how the

models are run), and *forecast accuracy*² (measured in terms of distance between a cyclone's forecasted position and the best track position).

Figure 1: Main techniques, technical sub-groups and examples of cyclone track forecasting techniques.

1.1 Tropical cyclone formation basins and their characteristics

All tropical waters, except for the South Atlantic and the eastern South Pacific Ocean (east of 140° W longitude) function as breeding grounds for low-pressure systems. The tropical and sub-tropical waters that support the formation and development of cyclones are called cyclone formation basins. There are seven such basins around the world (see also Figure 2):

1. Northwest Pacific basin
2. Northeast Pacific basin
3. North Atlantic basin
4. North Indian basin (Bay of Bengal and Arabian sea)
5. Southwest Pacific basin
6. Southeast Indian Ocean basin, and
7. Southwest Indian Ocean basin

These basins have different bottom-profile, and hence different water depth and mass and sea surface temperature, resulting in differences in the number of cyclones that are formed per year (Table 1) and the period of the year during which cyclones occur. In most of the basins, cyclones generally form during the seasonal transitional periods, but in the North Atlantic basin the

² Performances of different tropical cyclone track forecasting techniques in different basins are published each year. In this paper, for forecast accuracy we have relied on the annual tropical cyclone reports published by the Joint Typhoon Warning Center, and the forecast verification reports published by the National Hurricane Center.

scenario is considerably different; here most of the hurricanes are formed with the aid of the easterly winds from Africa (Arnault and Roux, 2011; Elsner and Kara, 1999).

Figure 2: Basins where tropical cyclones form on a regular basis.

The Northwest Pacific basin is considered to be the most active basin in the world (cyclone formation frequency is the highest in the world) (Table 1). Cyclones form here throughout the year—with a peak in frequency during a period from July to November. Cyclones in this basin generally move towards north/northwest after formation. The Philippines, Southeast Asia including China, Taiwan and Japan are all regions that are affected by cyclones formed in the Northwest Pacific basin. The Northeast Pacific basin is the second most active basin in the world. Cyclones are formed in this basin frequently during a period from about mid-May to end of November. Cyclones formed in this basin often hit the western parts of Mexico and Hawaii.

In the North Atlantic basin the period of cyclone formation stretches from about beginning of June to the end of November. The dominant cyclone track pattern in this basin is movement towards west and northwest after formation. Regions that are affected by the cyclones formed in this basin include the Caribbean, Central America, the Mexican gulf coasts of the United States and Mexico and parts of eastern Canada.

In the North Indian basin, cyclone formation period is between April and December with formation frequency reaching its peak in November. Basically, these are the transitional periods between seasons. Cyclones in this basin have a tendency to move initially in a west or northwest direction. After an initial period, they move northwards and sometimes they may also recurve northeastwards. The countries mostly affected by cyclones in this basin are Bangladesh, India and Myanmar.

From late October to early May is the period when cyclones are formed in the Southwest Pacific basin, with formation frequency peaking in late February and early March. After formation, cyclones in this basin usually move westward and affect the northeastern part of Australia.

The Southwest Indian Ocean and the Southeast Indian Ocean have similar cyclone formation periods ranging from late October to May. Cyclones formed in the Southeast Indian Ocean affect Northwestern Australia. Cyclones formed in the Southwest Indian Ocean tend to move west or southwestward and often hit Madagascar or parts of Southeastern Africa.

Globally, September is the most active period—when cyclone formation frequency is the highest—and May is the least active period—when cyclone formation frequency is the lowest (Sharkov, 2000).

Table 1: Annually averaged tropical storms and cyclone formation records by basin based on observations from 1968 to 1989 for the northern hemisphere and from 1968/69 to 1989/90 for the southern hemisphere (Neumann et al., 1993).

Basin	Tropical storms (maximum sustained wind speed >17 m/s)	Tropical cyclones (maximum sustained wind speed >33 m/s)
Northwest Pacific basin	26	16
Northeast Pacific basin	17	9
Southwest Indian Ocean basin	10	4
Southwest Pacific basin	9	4
North Atlantic basin	8	5
Southeast Indian Ocean basin	7	3
North Indian basin	5	3
Global total	82	44

1.2 Global pattern of tropical cyclone damage

Cyclones can cause both strong up-shore winds and flooding in coastal areas (CRED, 2009), but the actual damages inflicted depend on several factors, such as disaster management capability, geographical features of the basin, land-use pattern, and the socio-economic characteristics of the area. Although only 5% of the global tropical storms and 3% of the global tropical cyclones are formed in the North Indian basin (Table 1), the casualties here are as high as 80% of the global total (CRED, 2009; Debsarma, 2001, 2009). For example, the 1970 cyclone formed in the Bay of Bengal was the deadliest in the recorded history and caused more than 300 000 deaths in Bangladesh (Yang and Wang, 2005). Due to the shallow continental shelf at the coastline, cyclones that cross Bangladesh' coast are very often associated with severe surges. This situation is aggravated by the fact that the average height of the coastal land is less than 4 meters, with the consequence that surges can easily overflow the coastal areas and tend to inflict massive casualties and cause great property damage. In addition to Bangladesh, two neighboring countries are also frequently affected by tropical cyclones formed in the North Indian basin, namely India and Myanmar—although the number casualties caused by cyclones in these two countries are not as high as in Bangladesh.

Looking at property loss, the United States of America is the country where cyclones have caused most damage historically, followed by Japan at second place (CRED, 2009; Sheets, 1990). This contrasting scenario gives an impression that a country's level of development is closely related to the nature of damage caused by cyclones. A possible explanation for this could be that countries like the United States, Japan, and Australia have access to high-quality data

from several independent sources, such as radar, satellites and dropsondes, can afford to run computationally demanding cyclone forecasting techniques, and have the monetary and infrastructural resources to manage the crisis created by cyclones. For the above reasons, these countries are increasingly successful in reducing human casualties to a minimum.

In contrast, developing countries like Bangladesh, Myanmar, and India cannot afford expensive means for data collection, and would benefit greatly from computationally less demanding forecasting techniques that can be based on inexpensive data and that can be run on standard PCs. We think it is important to keep these criteria in mind, when comparing and evaluating various forecasting techniques.

In the concluding part of the article we have therefore highlighted a group of techniques among those discussed in the paper that is technically advanced, uses inexpensive data, is not computationally demanding, and is capable of producing forecasts with satisfactory accuracy. This relatively new group of techniques seems especially promising to cyclone-prone developing countries wishing to become more efficient in cyclone forecasting and emergency management, and will also work as an inexpensive and competitive complementary forecasting solution for countries that already have access to advanced forecasting techniques.

2 Averaging across cyclones

This type of techniques are also known as extrapolation, as they extrapolate and average the cyclone's current and recent-past movement (usually 6 to 12 hours back in time) to produce a forecast of the cyclone's future track. Extrapolation techniques are the simplest among all track forecasting techniques (Holland, 2009). All variables affecting cyclone movement are assumed to be constant and, as the variables are not changing, the cyclones are assumed to keep moving in the same direction as in the recent past. Forecast accuracy depends on precise selection of time-tagged recent-past positions of the current cyclone, as the previous positions and direction of the current cyclone are the only two factors that are governing the future movement here. For short term forecasts (12 to 24 hours ahead) extrapolation can be satisfactory, but for long term forecasts this family of cyclone forecasting techniques is not adequate (Jeffries et al., 1993).

Extrapolation (XTRP) is an example of the averaging technique and was used by the Joint Typhoon Warning Center (JTWC), Hawaii, USA. Starting from 1970 this technique was in use at JTWC for two decades to forecast cyclones formed in the Northwest Pacific basin. As each cyclone formation basin has unique climatological and geographical characteristics, the forecasting performance of otherwise equivalent forecasting techniques can differ considerably across basins. For this reason, the performance of different forecasting techniques can only be compared within the same basin. Performance of XTRP for both 24- and 48-hours forecast is similar to that of TYFOON (an analogue cyclone forecasting technique that was in operation at JTWC from 1970 to 1977) (Figure 3).

Figure 3: Performance of XTRP (an averaging across cyclones technique) and TYFOON (an analogue technique) in the Northwest Pacific basin

3 Statistical forecasting techniques

Statistical forecasting techniques are mostly regression based (Miller and Chase, 1966). Many statistical cyclone forecasting techniques have been developed over the years; they can be divided into the following five major types (Jeffries et al., 1993; Neumann, 1979a):

1. Climatologically-aware forecasting techniques
2. Climatology and persistence forecasting techniques (do not include synoptic data)
3. Statistical synoptic techniques
4. Steering airflow determination, and
5. Statistical-dynamical techniques³

Both short-time (24 hours) and long-time (72 hours) forecasts can be produced using statistical techniques. The data used for forecasting, also called the predictor data set, can be obtained from the present storm, from previous storms, synoptic analysis (see section 3.3) and numerical simulations. The main advantage of statistical techniques is that any combination of parameters or variables in the observed data set can be taken into account. Moreover the computational resources required to run statistical forecasting techniques are fairly low compared to the dynamical and numerical forecasting techniques (Lee and Liu, 2004; Neumann, 1985). Naturally, statistical techniques have also some drawbacks. Statistical regression methods produce forecasts that reflect the average behavior of storms in the predictor data set. For this reason, statistical techniques perform best when the present synoptic situation, as manifest in recent storm motion, does not depart too much from the normal climatology of the basin (Keenan, 1985). In addition, these techniques depend on good availability of data in order to reliably determine statistical trends in the cyclone tracks. Statistical techniques therefore tend to produce unreliable forecasts with strange motion characteristics in data-sparse regions or when they have to rely on bad past track data. In particular, statistical forecasting techniques can produce erroneous results when (Jeffries et al., 1993):

³ As statistical-dynamical techniques use predictors based on numerical simulations of the atmosphere that are produced by dynamical techniques, these techniques are discussed separately in section 5 after describing both statistical and dynamical techniques.

1. The forecast is pole-ward and eastward at low latitudes.
2. The forecast is equator-ward and eastward north of the subtropical ridge.
3. The forecast says the cyclone will stall or will get into a looping motion near the northern or southern subtropical ridges.
4. The main synoptic features deviate strongly from their normal climatological position.
5. The date of cyclone formation is outside the usual cyclone formation season for the basin.

3.1 Climatologically-aware forecasting techniques

Tropical cyclones formed in the same basin and during the same season have a tendency to move along similar tracks (Holland, 2009). These observations have led to the development of climatologically-aware forecasting techniques. The name refers to the fact that seasonal variations are taken into account when selecting similar past cyclones. The climatologically-aware forecasting techniques can be subdivided into the following three groups based on predictor selection criteria and the calculations used for forecasting (Chu, 1999b; Holland, 2009):

1. Cyclone forecasting through calculation of mean motion of past cyclones
2. Analogue cyclone forecasting techniques
3. Cyclone forecasting techniques using Markov chains

3.1.1 Cyclone forecasting through calculation of mean motion of past cyclones

These techniques consider the mean motion of all past tropical cyclones that have occurred within a similar time period as the current cyclone (e.g. during a specific season in previous years). The selected past cyclones are also required to have been located within a few degrees latitude and longitude of the present cyclone (Chin, 1957). It is assumed that whatever forces are affecting the present cyclone also have affected these past cyclones, and therefore the mean motion of these past cyclones will help to forecast the future motion of the current cyclone.

Climatology (CLIM), developed by JTWC, is a climatology forecasting technique that produces 24-, 48- and 72-hour forecasts through un-weighted averaging of the motion of previous cyclones in the same basin. CLIM was mainly developed for forecasting cyclone tracks in the Northwest Pacific basin but has also been used to forecast cyclones in the North Indian basin. For the Northwest Pacific basin, subsets of the historical storms that occurred between 1945 and 1981 are used as predictors. In contrast, for the North Indian basin, subsets of the cyclones that occurred between 1900 and 1981 are used as predictors. For 24-hour forecast CLIM performed similar in both of the basins but for 48- and 72-hour forecast the performance was better in the Northwest Pacific (Figure 4). In CLIM only those cyclones are considered as predictors that were formed in the same basin within $6^{\circ} \times 6^{\circ}$ latitude and longitude of the current cyclone's origin, and that were developed during the same month or months that include the days when the current cyclone was formed. If there are no past cyclones that satisfy both these criteria, then all the past cyclones developed within $6^{\circ} \times 6^{\circ}$ latitude and longitude of the current cyclone's origin are used as predictors (Jeffries et al., 1993).

A corresponding technique was developed by Lourensz (1981) for the Australian basin. This technique considers as predictors the mean and standard deviation of the movement of past

cyclones within 5° Marsden squares⁴ from the current cyclone. In this case the mean provides the forecast and the standard deviation provides an indicator of the uncertainty of the forecast.

Figure 4: Track forecast error produced by CLIM in the a. Northwest Pacific and b. North Indian basin

3.1.2 Analogue cyclone forecasting techniques

Analogue cyclone forecasting techniques differ from climatology mean motion detection techniques, in that they are more selective when choosing predictors (past cyclones). Instead of taking into account all the past cyclones that have previously occurred in the same basin, and within a specific spatial and temporal frame, analogue techniques additionally limit the set of predictors by criteria on the speed and direction of movement: These should be similar to the current cyclone's speed and movement direction.

HURRAN (Hope and Neumann, 1970), *TYFOON* (Jarrell and Somervell, 1970), *CYCLOGUE* (Annette, 1978), *TOTL* (Guard, 1992), and *TYAN93* (Jeffries et al., 1993) are some examples of analogue cyclone track forecasting techniques. *TYAN93* uses the same predictors as CLIM but instead of un-weighted averaging *TYAN93* produces forecasts through weighted averaging of the predictor dataset. *RECR*, developed by JTWC for the Northwest Pacific basin is technically similar to *TOTL* but has been developed to forecast re-curving cyclones only (Guard, 1992). Among all analogue forecasting techniques mentioned above, *HURRAN* is the most popular one, and became operational at the U. S. National Hurricane Center (NHC) in 1969. *HURRAN* or similar analogue techniques, like Eastern Pacific Analogue (EPANLG), have been used for several decades in meteorological offices around the world (Hope and Neumann, 1977). *HURRAN* selects analogue candidates based on the following criteria (Neumann, 1979a):

⁴ A spatial referencing system that divides the earth's surface into indexed squares. The world is divided into 936 Marsden squares where each square has a size of 10° latitude x 10° longitude.

1. All the cyclones of the basin that occurred within 15 days of the current cyclone date
2. Passed within 2.5° of latitude of the current cyclone
3. Moved in a direction that lies within 22.5° of the direction of the current cyclone
4. Moved with a speed which is within 5 knots (2.57 m/s) of the speed of the current cyclone

Though the overall performance of analogue forecasting techniques in the North Atlantic basin was poor compared to other cyclone track forecasting techniques (Figure 5), such as climatology and persistence (CLIPER), synoptic (NHC67 and NHC72), statistical-dynamical (NHC73), and barotropic (SANBAR) techniques, analogue techniques are popular, partially due to the presentation of forecasts in terms of probability ellipses (Neumann, 1979a). These probability ellipses provide useful diagnostic information at a minimal cost and using a minimum of computational resources (Simpson, 1971).

Figure 5: Performance of HURRAN compared to NHC67, NHC72, NHC73, CLIPER, and SANBAR in the North Atlantic basin for a. 12 hours b. 24 hours c. 48 hours and d. 72 hours

Sievers et al. (2000) have developed an analogue ensemble⁵ forecasting technique that, in contrast to HURRAN, is self-adapting in terms of selecting historical analogues. The concepts that are used in this analogue technique were borrowed from time series nonlinear chaotic system prediction developed by Fraedrich and Rückert (1998) and Sauer et al. (1991). The ensemble technique of Sievers et al. (2000) consists of four successive steps:

Step A: The present cyclone's state space (development in time) is reconstructed from observational data. The reconstructed state space will contain a sequence of states labeled with the times of the corresponding observations.

⁵ Ensemble forecasting is a numerical prediction method that generates a representative sample of the possible future states of a dynamic system.

Step B: The Euclidean distance between previous analogues and the presently observed cyclone is defined. Step A and B together form the basis for this analogue forecasting technique.

Step C: The various analogues are combined in a weighted sum. These weights are optimized using the method for optimization suggested by Fraedrich and Rückert (1998), and later modified by Sievers et al. (2000) through the inclusion of ensemble forecasts.

Step D: At this last stage the forecast is optimized by repeated use of a heuristic learning rule (the learning rule is heuristic in the sense that it is not guaranteed to improve the forecast).

The climatology and persistence technique called CLIPER (see section 3.2.1) is generally used as a point of reference for evaluating the performance of other forecasting techniques. Also the self-adapting analogue ensemble technique described above was evaluated using CLIPER as a reference. Compared to CLIPER, the self-adapting analogue ensemble technique produces 15-20% more accurate forecasts for the East Pacific basin. However, for the Atlantic Ocean, CLIPER yields better results than this self-adapting technique (Sievers et al., 2000). Following the success of this technique, a self-adapting technique has also been developed and successfully used to forecast cyclone track in the Australian region (Fraedrich et al., 2003).

3.1.3 Cyclone forecasting techniques based on Markov chains

Markov chains refer to a sequence of states in which each state depends only on the previous state (Elsner et al., 2004). For cyclone track forecasting, Markov chains can be defined on the basis of the climatological characteristics of previous cyclones that arose in the same ocean basin during the same time of year (Leslie et al., 1992). A Markov chain that is produced in this way contains transition probabilities indicating if the cyclone will change its speed and direction in a certain way. Once the transition probabilities for the previous cyclones have been determined, the current cyclone can be forecasted using the same transition probabilities.

3.2 Climatology and persistence techniques

Under constant atmospheric conditions a cyclone continues to move in the same direction. The group of techniques that has been developed based on this observation is known as averaging across occurrences or extrapolation (see section 2). These techniques can produce satisfactory forecasts for short-term periods (usually for 6 to 12 hours). As the atmospheric situation does not remain constant within a cyclonic system, for long-term forecasts (from 24 to 72 hours) it is necessary to know which atmospheric forces are governing the cyclone track. This information can be obtained through assessing historical cyclone tracks in the same basin as the current cyclone, and under similar atmospheric conditions (climatological data) as the currently ruling ones. The group of techniques that considers historical data under similar atmospheric conditions when forecasting the current cyclone track is known as climatologically-aware forecasting techniques (see section 3.1). These techniques show satisfactory performance for long-term forecasts.

Climatology and persistence techniques differ from climatology-aware techniques in that they combine information both from recent and historical cyclones to get the advantages of short and long-term forecasts in a single technique. Moreover, the operation of climatology and persistence techniques is simpler than the climatologically-aware forecasting techniques.

Climatologically-aware techniques read all the historical cyclone track data each time they are run. In contrast, climatology and persistence techniques use the historical cyclone track data only during the development of the regression equations (Neumann, 1979a).

The first step towards a combined climatology and persistence technique was taken at the Royal Observatory in Hong Kong, when forecasts based on climatology and persistence were combined with equal weights (Bell, 1962). Climatology and persistence techniques were the best performing among all forecasting techniques in those days when forecasting techniques capable of considering observational data from different geopotential heights⁶ were not available, and are still today in use at different meteorological offices, either stand-alone or as a component of other methods (Holland, 2009).

3.2.1 CLIPER

CLIPER (CLImatology and PERsistence) was developed by Neumann (1972) as an alternative to HURRAN to forecast cyclones formed in the Atlantic basin. A corresponding technique known as East Pacific CLIPER (*EPCLPR*) was developed for the East Pacific basin. The prediction equations employed by CLIPER are derived using linear regression and can produce forecasts for up to 72 hours. The computational resources required to run these techniques are fairly low. Climatology and persistence techniques can be run on IBM-XT or personal computers with higher configurations (Holland, 2009). As regression is used to produce the forecasts in CLIPER and EPCLPR, these techniques can produce satisfactory forecasts given insufficient data and in anomalous, irregular situations (Neumann, 1979a). In contrast, the accuracy of HURRAN (see section 3.1.2) totally depends on the availability of suitable analogue candidates, so when suitable analogue candidates are not available, HURRAN fails to produce cyclone forecasts. A combination of the following eight predictors are taken into account when cyclones are forecasted using CLIPER (Neumann, 1979a):

1. Latitude of the current cyclone
2. Longitude of the current cyclone
3. Current cyclone u-component of motion (represents the east-west component of the wind motion driving the cyclone)
4. 12 hour old u-component of motion
5. Current cyclone v-component of motion (represents the north-south component of the wind motion)
6. 12 hour old v-component of motion
7. Day number (Julian date)
8. Maximum sustained wind speed (period during which the temporarily maximum wind speed is sustained, measured in minutes)

All these predictors, except number 8, are also used by EPCLPR to forecast cyclones in the East Pacific basin (Neumann, 1979a). Sometimes, more than eight predictors are used for

⁶ Geopotential height represents the actual height (in meters) of a pressure surface measured from mean sea-level.

forecasting, depending on the length of the forecast period. For short-term forecasts (24 hours), only the eight predictors mentioned above are used. For long-term forecasts (48 to 72 hours), the products and cross-products of the 8 predictors listed above are also considered. These are taken from historical records and more emphasis is given to them than to data from the current cyclone (Holland, 2009; Neumann, 1979a).

Northwest Pacific Climatology and Persistence (*WPCLPR* or *CLIP*) used by JWTC is also a climatology and persistence technique. Similarly to CLIPER, this technique uses climatological information, current position of the cyclone and past 12 and 24 hour track data for the current cyclone as predictors. Twelve regression equations are used in this model. Six of these provide zonal speed forecast (speed in an east-west direction) and the remaining six equations are used to forecast meridional speed (speed in the north-south direction). These two components are combined to generate 24-, 48- and 72-hour forecasts (Jeffries et al., 1993; Xu and Neumann, 1985). For long-term forecasts (72 hours), climatology and persistence techniques perform better in the Northwest Pacific basin than in the North Atlantic basin. In contrast, for shorter-term 24- and 48-hour forecasts the performances of these techniques are comparable in both of the basins (Figure 6).

Cyclone forecasts produced by climatology and persistence techniques can also be presented in the form of probability ellipses, like in the analogue techniques, but this option was first incorporated into the version of climatology and persistence techniques developed for the North Indian basin (Neumann and Mandal, 1978). Climatology and persistence techniques are in many respects similar to analogue forecasting techniques. However, the simplicity, robustness, and improved performance of climatology and persistence techniques compared to the analogue ones have made the CLIPER-class techniques the preferred alternative over the analogue techniques.

Figure 6: Track forecast error produced by climatology and persistence techniques for 24, 48, and 72 hours in the a. North Atlantic basin and b. Northwest Pacific basin

3.3 Statistical synoptic techniques

Height over sea level and air pressure are inversely related. This gradual reduction of air pressure with increasing height may also cause other changes in atmospheric variables. Taking into

account atmospheric information from different pressure levels may increase the accuracy of the cyclone forecasting techniques. This insight about the importance of the variation of air pressure levels at different geopotential heights contributed to the development of statistical synoptic techniques. These techniques consider including current and 24 hours old upper-level geopotential height data, as an important factor in cyclone forecasting. The additional use of geopotential height data as one of the predictors has made these techniques stand out from the climatology and persistence techniques. A particular geopotential height or a combination of heights from the upper levels is systematically selected through a stepwise screening process. Data from these heights are represented in a 3D-grid where the cyclone is always kept at the center (Neumann, 1979a). Beside the implementation of geopotential height data as one of the predictors (common for all statistical synoptic techniques) some synoptic techniques also use different stratification methods mainly based on the cyclone formation location, initial movement direction, and initial movement speed (slow or fast). For short- and medium-term forecast (≤ 48 hours) these statistical and synoptic techniques perform slightly better than climatology and persistence techniques. For longer time periods (> 48 hours) climatology and persistence techniques perform better than the synoptic ones (Neumann, 1979a). In the following, we briefly describe a few examples of statistical synoptic techniques.

3.3.1 Veigas-Miller

The Veigas-Miller technique, developed by Veigas et al. (1959), uses a multiple-screening linear-regression method (Miller, 1958) to forecast cyclones. Instead of looking at upper level air observations, this technique uses another predictor: the sea-level pressure of selected points making up a $5^\circ \times 5^\circ$ grid extending over 30 degrees of latitude and 60 degrees of longitude (Tse, 1970). Development of this method was based on observations from 447 cyclones and a subset of 91 sea-level pressure readings in the Atlantic basin (Chin, 1965; Miller and Chase, 1966), but the method showed good performance also at cyclone forecasting in the Pacific basin (Chin, 1965). The multiple-screening linear-regression method used in this technique is simple to calculate and as sea-level pressure is the only synoptic information considered, forecasts produced by this technique are effective for longer time periods compared to synoptic techniques that use upper level atmospheric information (Chin, 1965). One disadvantage of this method is that it is sensitive to the location of the storm center within the analysis grid. If the storm center is positioned erroneously when the grid is set up, this technique cannot be expected to produce reliable forecasts (Gentry, 1963). For 24-hour forecast the average error produced by this technique in the Atlantic basin was 185 kilometers (Chin, 1965). A similar technique was developed by Wiederanders (1961) for the Northwest Pacific basin, with a forecast accuracy at par with the Veigas-Miller technique.

3.3.2 Chen-Elsberry

This technique was developed for the Northwest Pacific basin, and in this basin the technique performs better than WPCLPR (Chen et al., 1999). The same eight predictors are used as in WPCLPR: present cyclone position and intensity, past 12 hour and 24 hour cyclone positions and intensity, and date. Chen and coworkers developed this technique as an easy-to-use and operationally fast forecasting technique that allows the forecaster's synoptic knowledge to be used. This means that the mean motion of past cyclones having a similar synoptic pattern is considered as an additional predictor. From the classification of synoptic patterns and synoptic regions of the Northwest Pacific (Carr and Elsberry, 1994), this technique considers only two dominant synoptic patterns: (a) the standard pattern and dominant ridge region (S/DR) and (b)

poleward (P) pattern and the poleward-oriented (PO) region (P/PO) as synoptic information. These patterns cover 73% of all the observed synoptic situations (Chen et al., 1999).

The Chen-Elsberry technique differs from the Veigas-Miller technique in terms of:

1. *Gridding*—Veigas-Miller uses a 5°x5° gridding system. In contrast, the Chen-Elsberry technique does not use any gridding.
2. *Synoptic information*—The Veigas-Miller technique uses sea-level pressure as one of the predictors. Instead, Chen-Elsberry considers predefined synoptic patterns as predictors.
3. *Predictors* (other than synoptic information)—The Veigas-Miller technique is based on 447 historical cyclones in the Atlantic basin. As opposed to this, Chen-Elsberry uses the same predictors as WPCLPR.

NHC67 and *NHC72* (for the Atlantic basin) and *EPHC77* (for the eastern Pacific basin) are examples of synoptic cyclone forecasting techniques developed by the U. S. National Hurricane Center (NHC). These techniques use similar methodology for synoptic predictor selection, but differ from each other in terms of types of predictors and the method of stratification. Atmospheric data from the 1000, 700 and 500 mbar geopotential height levels are used as synoptic predictors by *NHC67* and *NHC72*. In contrast, *EPHC77* uses predictors only from the 500 mbar level (Neumann, 1979a).

The location of cyclone formation, the initial movement speed, and initial movement direction have considerable influence on the development of future cyclone tracks within a basin. The use of these positional and initial directional variations can play an important role in improving the performance of statistical synoptic techniques (Neumann, 1979a). *NHC67*, *NHC72*, and *EPHC77* all use different stratification methods in order to improve the forecast accuracy. The stratification method used by *NHC67* splits the predictor datasets according to if the cyclone's location of origin is south or north of 27.5° N latitude. Through stratification, the forecast is adapted to the climatological differences of these two zones. Moreover predictors are selected in different order and/or different weights are assigned to the different predictors to forecast slow (between 13 and 24 km/h) and fast moving cyclones (more than 24 km/h) (Miller et al., 1968). In contrast the stratification methods used by *NHC72* and *EPHC77* split the predictor datasets with respect to the initial direction of motion of the cyclone. If the cyclones are located in the deep tropics (south of 18°N) and over the Western Caribbean or the Gulf of Mexico (Neumann, 1979a) then a different stratification is used.

When comparing forecasting performance, in the North Atlantic basin, *NHC72* performs slightly better than *NHC67* for 24-, 48-, and 72-hour forecasts; for 12-hour forecasts, performance of these techniques is almost the same (Figure 5).

3.4 Cyclone forecasting through steering airflow determination

Similarly to the statistical synoptic techniques, cyclone forecasting through steering airflow determination also uses atmospheric information from different atmospheric levels, with the basic difference that steering airflow determination techniques do not take into account climatological and persistence predictors during analysis. Instead, these techniques consider cyclones as a vortex point surrounded by airflow in such a way that the direction and speed of the cyclone can be approximated by those of its surrounding winds. To determine the appropriate air pressure level or levels (steering heights) that will control the direction and speed of the cyclone, an air pressure chart is compiled showing the air pressure gradients across the cyclone for various air pressure levels. Using these charts, particular air pressure levels are identified as

the steering levels where the speed and direction of surrounding winds best correlate with those of the cyclone's present movement (Holland, 2009).

Although different forecasting techniques would identify different air pressure levels as steering levels (Miller and Moore, 1960; Renard et al., 1973; Riehl and Shafer, 1944; Tse, 1966), it is widely accepted that the airflows in the mid-troposphere (usually between 500 and 700 mbar) are the best for forecasting cyclone movement (Chan and Gray, 1982; George and Gray, 1976). After studying cyclones in three different basins (Northwest Pacific, North Atlantic, and Southwest Pacific) Chan and Gray (1982) concluded that tropical cyclones in the northern hemisphere move approximately 10-20° to the left of their surrounding mid-tropospheric flow. In contrast, cyclones in the southern hemisphere move circa 10° to the right of the surrounding flow. In both hemispheres, cyclones move slightly faster than these surrounding tropospheric airflows. This general relationship between cyclone track and speed and steering airflow is sometimes modified by other factors, such as vertical wind shear (Chan and Gray, 1982).

Even though the winds at mid-tropospheric levels (500 and 700 mbar) seem to be a good indicator for the movement of the cyclone, to achieve reasonable forecasting accuracy, the following aspects also need to be determined (Chan and Gray, 1982):

1. Starting from the center and going outward: At which distance does the surrounding airflow correlate best with the movement of the cyclone?
2. In what way does this correlation vary between cyclones of different intensities, formed at different latitudes in different oceans, moving in different directions and with different speeds?

Airflows surrounding the cyclone can explain up to 80% of the variance of cyclone motion; which means that airflow estimation provides valuable support for cyclone track forecast (Keenan, 1982; Neumann, 1979b). However, research during the past decade has shown that other forms of interaction between the cyclone and its environment can also have a noticeable impact on its motion, which means that the earlier simplistic view of steering currents may be inaccurate (Dong and Neumann, 1986; Fiorino and Elsberry, 1989; Wang and Holland, 1996a; Wang and Holland, 1996b; Wang and Holland, 1996c).

Performance between the steering airflow determination techniques vary due to the pressure levels these techniques are considering information from, as well as the ability of the various techniques to capture the surrounding atmospheric situation, and their ability to relate these atmospheric characteristics to the forecasted cyclone's track (Tse, 1966). For example, the steering airflow determination technique developed by Miller and Moore (Miller and Moore, 1960) has an average error of 213 kilometers in the Northwest Pacific basin for 24-hours forecasts. In contrast Tse's technique performs considerably better, with an average forecast error of 161 kilometers for 24-hour forecasts in the same basin (Tse, 1966).

3.5 Techniques based on satellite image interpretation

Cyclones usually move large distances over the tropical oceans before they make landfall. As cyclones spend most of their lifetime over tropical oceans, detailed information throughout their life cycle cannot be collected using ground based observations. At the same time, there is a need to observe these cyclones in as much detail as possible, since knowledge of their formation and previous movement pattern is important when producing cyclone track and landfall forecasts (Dvorak, 1975). In this situation satellite images can provide valuable information for cyclone

track forecast (Goerss and Hogan, 2006; Goerss, 2008; Kidder et al., 2000; Marshall, 1998; Sandeep et al., 2006). Though the use of satellite images is common for most of the operational cyclone forecasting techniques today, some techniques use satellite images as the primary data source when producing cyclone track forecasts. As satellite-image-based techniques use statistical equations to interpret satellite images and produce forecast for cyclones, they are discussed under statistical techniques.

Besides dedicated techniques that use satellite images as the primary data source, most other operational forecasting techniques use satellite images to enhance forecast accuracy. For example, cloud and water vapor data recorded by satellites have been used to improve the accuracy of numerical forecasts in the Australian region since the early 1980s (Le et al., 1985); satellite-derived wind information has been used to improve the forecast accuracy both for tropical cyclones (Goerss et al., 1998; Isaksen and Stoffelen, 2000; Langland et al., 2009; Leslie et al., 1998; Ma and Tan, 2009; Tomassini et al., 1998; Velden et al., 1992; Wang et al., 2006) and extratropical cyclones (Xiao et al., 2002). Moreover, the internal structure of a cyclone and the amount of water stored in it can be extracted through analyzing satellite images (Kokhanovsky and Hoyningen-Huene, 2004).

As the forecasts based only on satellite data are influenced by the spatial and temporal distribution of satellite observations and are dependent on the continuous availability of noise-free images (Le et al., 1996; Le et al., 1996; Le et al., 1997) these techniques have not received wide acceptance and are not used as the primary cyclone forecasting technique at meteorological offices worldwide (Holland, 2009). Satellite-image-based cyclone forecasting techniques involve interpretation of cloud patterns that are associated with the cyclone (Ma and Tan, 2009); these patterns can help determine the exact location of a cyclone (Wei and Jing, 2010), and can indicate specific types of motion, or changes in track. For example, changes in the track of cyclones have been observed to correlate with rotational changes in the storm's overall features, for example, overall cloud patterns. The angular rotation of the overall features during the past 24 hours can be added to a 24 hour persistence forecast to yield an improved 24-hour forecast (Beer and Giannini, 1980; Fett and Brand, 1975). This technique can predict short-term (12 to 24 hour) track of cyclones with acceptable accuracy (Fett and Brand, 1975).

Another satellite-image-based cyclone forecasting technique, developed by Lajoie and Nicholls (1974) and further extended by Lajoie (1976), use an elaborate cloud model (Figure 7) and the following rules to forecast cyclone track for the coming 12 hours (Lajoie, 1976):

1. A tropical cyclone will not move, nor curve in a direction towards a cumulonimbus-cloud-free sector. If it starts moving towards such a sector, it will curve rapidly away from that direction.
2. A tropical cyclone having a single outer cloud band will move or curve within twelve hours towards a line joining the present position of the vortex center and the present position of the most developed cumulonimbus cluster at or near the downstream end of the outer cloud band.
3. When a tropical cyclone has two outer cloud bands and is moving towards the most developed cumulonimbus cluster near the downstream end of one outer cloud band, it will curve within twelve hours towards a line joining the present position of the vortex center to the present position of the most developed cumulonimbus cluster near the downstream end of the other outer cloud band.

Figure 7: Typical cloud patterns associated with northern hemisphere tropical cyclones. Clouds within the small ring represent the main cyclone body. The cyclone eye located at the center of the image is usually cloud free. Clouds at the top of the ring are cumulonimbus clouds, not associated with the main cyclone body. Clouds at the bottom represent outer cloud bands that do not indicate any particular movement direction. Clouds to the right of the ring indicate the direction of movement. Adapted from Lajoie and Nicholls (1974).

Forecasting cyclones using this technique requires satellite image interpretation skills and can only produce forecasts for cyclones for which the features mentioned above are visible in the satellite image. Nevertheless, manual satellite-image-based techniques can provide good result, especially when the revisit period of the satellite is short (in case of polar orbiting satellites) or if the satellite is geostationary.

3.5.1 Empirical forecasting techniques

Empirical forecasting techniques rely on the expertise of the forecaster in recognizing the cyclone movement pattern. As a result, forecasts using these techniques are greatly influenced by the level of experience of the forecaster. The expertise of the forecaster in recognizing patterns can eliminate major errors associated with missed re-curving and acceleration of storms into the mid-latitudes. The main weakness of these techniques is the time required for the forecaster to gain the necessary level of expertise (Jeffries et al., 1993; Chu, 1999b). Examples of empirical forecasting techniques include (Guard, 1992):

The Dvorak technique: Dvorak (1972) developed his technique mainly to quantitatively analyze and forecast cyclone intensity, but the technique can also be used to forecast cyclone track. Satellite images of visible and infrared frequency range are the only predictors that are used in this technique. Characteristic cloud patterns associated with the cyclone normally signify different stages of development and provide a good indication of the deepening or weakening of the cyclone (Dvorak, 1975). Beside the cyclone's intensity, the cyclone's near-future and next 24-hour motion can also be estimated through interpretation of cloud patterns present in the satellite image (Dvorak, 1984).

Martin/Holland: The Martin/Holland technique (Guard, 1992) is based on earlier work of Gregory Holland (Holland, 1980). This technique uses enhanced infrared satellite images to

derive central cloud size, cyclone intensity, and to produce a wind profile. The wind profile is then adjusted for expansion/contraction (associated with deepening or weakening of the cyclone), and is also adjusted for extra-tropical transitions (the changing of a tropical cyclone into a mid-latitude depression) and land interaction when necessary (Chu, 1999a). Martin and Holland also bring forth the importance of the 30, 50 and 100 knot (15, 26 and 51 m/sec) wind radii⁷ around cyclones which are suitable for 24-, 48- and 72-hour forecasts (Guard, 1992; Chu, 1999a).

The typhoon acceleration prediction technique: The Typhoon Acceleration Prediction Technique (TAPT) (Weir, 1982) uses upper-tropospheric and surface wind fields to estimate the intensification of a cyclone associated with the mid-latitude westerly winds. Output from this technique includes estimates for the duration of wind acceleration, upper limits of the wind and probable track of the cyclone (Guard, 1992).

3.5.2 Techniques using artificial neural networks

In cyclone monitoring and forecasting, satellites have become one of the most important platforms for collecting information about the cyclone and its surrounding environment. Identification of variations in the very low contrast cloud features associated with cyclones, integration of information collected through various sensors, and identification of spectral and spatial patterns have proved to be a challenging task to many traditional forecasting techniques (Lee and Liu, 2004; Villmann et al., 2003). Although there are techniques (e.g., numerical, and statistical-dynamical) that have such capabilities, these traditional techniques are complex, require high-end computers to run, and are vulnerable to inaccurate initial values (Jeffries et al., 1993). In addition, these remotely sensed data are usually very large in size and are frequently noisy. The complexity of the data and the computational demands of other forecasting techniques have motivated research into novel approaches for processing remotely sensed images to forecast cyclones. One of these emerging approaches is to use of Artificial Neural Networks (ANNs) for data processing. ANN-based cyclone forecasting techniques are characterized by the following important features (Villmann et al., 2003):

1. *Adaptivity*: the ability to continuously change the system's internal representations (network structure and connection weights) to suit new data or information that becomes available.
2. *Robustness*: seamless handling of missing, noisy or confused data to the extent that these data can be auto-completed and corrected on the basis of statistical regularities found in previously processed data.
3. *Power/speed*: handling of large data volumes within an acceptable time frame due to inherent parallelism.
4. *Non-linearity*: the ability to represent non-linear functions or mappings.

These properties render artificial neural networks useful and efficient for analyzing satellite data for cyclone track and intensity forecasting. In addition to these inherent characteristics that made neural networks useful for cyclone track and intensity forecasting, there are also other features of neural-network-based forecasting techniques that make these techniques inexpensive

⁷ Wind radii represent the maximum radial extent of winds with a given speed around the cyclone.

in terms of data usage and computational resource requirements. Artificial neural networks are advantageous in the following sense:

1. Use of satellite images as input that are widely available and mostly free of cost
2. Neural-network-based techniques can easily be run on standard desktop PCs. So these techniques are computationally inexpensive
3. Although considerable time is required to train the network using all the historical satellite images, once the network is trained few minutes or fractions of a minute is required to produce cyclone track and intensity forecasts
4. Neural network based techniques are capable of producing forecasts with acceptable accuracy

The use of artificial neural networks as a cyclone track and intensity forecasting technique is fairly recent compared to other forecasting techniques. As these techniques are still in development and require a huge effort to build and train, they are not as widely adopted as other forecasting techniques. In the following, we briefly describe a few examples where artificial neural network techniques have been successfully used for cyclone track forecasting.

3.5.2.1 Nonlinear neural network

Pickle (1991) tested two pattern recognition techniques where he related short-term track (24 hours) and intensification of tropical cyclones to recurring patterns within the surrounding geopotential heights and wind fields. The first technique was based on a linear correlation analysis. The second technique used a nonlinear ANN, which was trained using backpropagation of error.

Both types of pattern recognition techniques were developed on the basis of upper-atmospheric sounding data from 30 stations located throughout the western North Pacific region (for the period 1978 to 1989). The data that were used in this study included wind speed and direction and geopotential heights of five different air pressure levels (700, 500, 400, 300, and 200 mbar) recorded by the sounding instrument. Sounding data from 1978 to 1987 were used as developmental dataset (training data) and sounding data for the period 1988 to 1989 were used as test dataset. As both training and testing of the techniques require the availability of historical data showing the actual track and intensity development of the cyclone in question, cyclone best track data prepared by JTWC, consisting of six-hourly cyclone intensities (≥ 63 km/h) and positions for the period 1978 to 1989 were used as targets during training and testing.

The ability of the linear correlation technique and the artificial neural network technique to forecast cyclone track was compared to the forecasting ability of persistence techniques and three other forecasting techniques (OTCM, CSUM, and HPAC) used by JTWC. Pickle also compared the short-term intensity forecast capability of these two techniques with other intensity forecasting techniques employed at JTWC. For short-term track forecasts, the results generated by the correlation analysis and by the ANN were similar to those produced by persistence and CSUM forecasting techniques and worse than those of OTCM and HPAC (Pickle, 1991). When only cyclone intensity forecasts were considered, the ANN performed better than all other climatology and persistence techniques used at JTWC at that time.

3.5.2.2 Hybrid radial-basis-function network

The Hybrid Radial-Basis Function (HRBF) network technique developed by Lee and Liu (2000) can automatically identify cyclones from satellite images and can produce track and intensity forecasts with remarkable accuracy. This technique works in two modules. The first module is devoted to extracting cloud patterns from satellite images and detecting intensity features from the extracted pattern and the second module is specialized for mining the information obtained from module 1 and producing intensity and track forecast based on that information.

Module 1: The Neural Oscillatory-based Elastic Graph dynamic link Model (NOEGM) developed by Lee and Liu (1999, 2002) can automatically recognize and classify different cloud patterns from satellite images and associate these with various cyclone intensity. This module is further divided into three different sub-modules:

Sub-module 1: Extraction of the cloud patterns of tropical cyclones using Gabor filters. Gabor filters are used as detectors of small, localized cloud stretches or blobs in the satellite image. As these detectors are localized, a large number of Gabor filters are used to cover the whole image (the exact number depends on the size of the image and the size of each filter's receptive field). The outputs from these detectors are then combined and used to characterize the cloud patterns at larger scales in the image.

Sub-module 2: Image segmentation using a Composite Neural Oscillatory Model (CNOM)

Sub-module 3: Pattern recognition and classification using NOEGM

Module 2: Tropical cyclone track and intensity forecasting using a HRBF network. Once the patterns associated with tropical cyclones are extracted by the first module, the patterns are matched and forecasts are produced. HRBF integrates the following two useful features into the conventional RBF network to enhance its forecasting performance (Lee and Liu, 2000):

1. Structural learning with weight decay
2. Temporal difference learning

Time series of tropical cyclone images were used for the study. The 120 images were randomly divided into 2 sets. The first image set was used for training and the second set was used for testing. Compared to OTCM (see section 4.2.4), this HRBF technique can forecast cyclone track with 30% higher accuracy. To implement the whole system and to evaluate the performance, a single Sun Sparc 20 workstation was used (Lee and Liu, 2000).

When it comes to intensity, this technique uses the Dvorak's T number as intensity scale. In contrast to Dvorak's technique however, instead of relying on subjective human reasoning, HRBF accomplishes the necessary reasoning steps in a fully automated fashion.

When visible satellite images are used, this HRBF artificial neural network forecasting technique can determine cyclone intensity with 82% accuracy—meaning that the forecasts produced by the network on the basis of the test images were correct in 82% of the cases. When enhanced infrared cyclone images are used, cyclone intensity forecast accuracy rises to 95%. As mentioned earlier, this forecasting technique employs Dvorak's intensity scale, which entails that the technique can be used as a computationally efficient, automated alternative to Dvorak's technique.

3.5.2.3 *iJADE WeatherMAN*

iJADE WeatherMAN (Lee and Liu, 2004) is not a cyclone forecasting system as such but an *intelligent-agent-based* system that is integrated with a fuzzy artificial neural network to automate weather information gathering, filtering and forecasting. Unlike other agent-based systems like those based on *IBM Aglets* and *Java Agent Development Framework (JADE)* which focus on multi agent communication and autonomous operations, the aim of iJADE is to provide a comprehensive intelligent-agent-based framework for web-mining applications (Lee and Liu, 2004). This framework works in a two level architecture: (a) iJADE system level, and (b) iJADE data level.

The job of the data level is to collect information from different sources and process it using artificial neural networks. Data that are integrated and processed at data level include six-hourly readings of temperature, dew-point temperature, relative humidity, hourly rainfall, mean wind speed, 60 minute prevailing wind direction, and mean sea-level pressure. The weather forecasts that are produced are visualized to the different clients (at weather stations or to the general public) with the aid of the system level component. This technique has successfully been applied to rainfall forecasting and it is intended to be used in the future to forecast other weather phenomena like thunderstorms and cyclones.

3.5.2.4 *SEMO-MAMO*

Feng and Liu (2004) have developed a three-phase prototype that uses a modified Hausdorff distance as a similarity metric to compare tropical cyclone images. This technique is similar to the first module of the HRBF network developed by Lee and Liu (2000). Both SEMO-MAMO and HRBF use contours to identify cloud patterns in satellite images. In Feng and Liu's system, the contours that are extracted in the first phase are assigned weights in the second phase. Finally, in the third phase, a modified Hausdorff distance is used to compare two sets of contours, where the first set is obtained through pre-processing in the previous phases and the second set comprises Dvorak templates capturing various cyclone intensity levels.

Feng and Liu implemented their technique using 40 tropical cyclone satellite images and compared the result with Dvorak template images. When using the Dvorak templates as reference images, this technique can produce cyclone forecasts with 100% accuracy. If the extracted contours are matched with other unprocessed satellite images instead of the Dvorak templates, the accuracy decreases to 74.32%. To carry out the comparison a 2.26 GHz Intel Pentium CPU with 512 mb RAM took only 43.09 seconds when Dvorak templates were used and 83.375 seconds when other satellite images were used instead (Feng and Liu, 2004). The main advantage of this technique is that it automates the comparison of satellite images, which is used as a basis for cyclone intensity forecasting, and implements this comparison with high computational speed and high accuracy.

3.5.2.5 *Genetic learning artificial neural network*

Different techniques used for cyclone track forecasting have a varying ability to describe the physical processes in the atmosphere. Due to this varying ability to describe the physical atmospheric processes and characteristics of different cyclone formation basins, cyclone track forecasting by numerical models vary considerably (Yang and Wang, 2005). The great number of differing forecasts shared among meteorological offices makes the chief meteorologists' task of arriving at a composite forecast exceedingly difficult. To solve this problem Yang and Wang

(2005) developed a Genetic Learning Artificial Neural Network (GLANN) that learns to assemble a composite track forecast based on the best fit with historical track data. A huge data set of 27600 typhoon tracks formed in the Northwest Pacific basin between 1884 and 2002 has been used to train the network. A smaller number of typhoon tracks from recent years were used to test the network's forecasting performance.

This technique for combining performs better than the forecasting techniques used at the China Central Meteorological Office, the Japan Meteorological Agency, and the Guam Forecast Office, USA. For 10 test cases of typhoons exhibiting unusual movement characteristics, the average error produced by Yang and Wang's technique for 24-hour forecasts was 153.29 km. The corresponding forecast error by the China Central Meteorological Office was 177.6 km, by the Japan meteorological agency was 157.15 km, and by the Guam forecast office, the error was 167.14 km (Yang and Wang, 2005).

3.5.2.6 Ali and coworkers

Ali et al. (2007) present a neural-network-based technique dedicated to forecasting cyclones in the north Indian Ocean. Ali and coworkers used TC track data⁸ from the past 32 years (1971-2002) to train the network. Using this vast amount of data for training the network, the network was forced to learn the correlations between satellite-based data and cyclone track. This artificial neural network was then fed with past 12 hour observations (at 6 hour intervals) to make a 24-hour forecast of forthcoming cyclone positions. A similar ANN-based technique was developed by Johnson and Lin (1995) for the North Atlantic basin. This technique is able to produce track forecast for the next six hours with good accuracy.

3.5.2.7 Biologically-based hierarchical artificial neural network technique

Kovordányi and Roy (2009) present a technique which uses a multi-layer artificial neural network for cyclone track forecasting. This technique works through two phases (training and testing). During the training phase the network learns to detect statistically indicative information from NOAA-AVHRR satellite images. In the testing phase the network interprets new sets of images (in this case new satellite images) and produces forecasts using knowledge of reoccurring patterns that the network extracted during the training phase.

Original NOAA-AVHRR cyclone satellite images were downsized to 66 x 66 pixels and converted into gray-scale before feeding the images into the network. Correct detection of cyclone track by the network during testing depends on the number of similar patterns the network has experienced during the training phase. In order to provide the network with a broader basis of experience, the original cyclone images were artificially rotated clockwise in 45° increments, each rotated image was then zoomed in three different ways (using 0.8, 1, and 1.2 zoom factors), and finally each rotated and zoomed image was shifted in position within the input frame by zero, one, or two pixels in eight directions (north, south, east, west, northeast, etc.) to add positional variations. After processing this training set, the artificial neural network could forecast the track of novel cyclones in 99% of the cases.

⁸ Observed cyclone track data archived by JTWC

3.6 Forecast optimization based on Kalman filters

Kalman filters are a set of mathematical equations that provide an efficient computational means for estimating the state of a process, in a way that minimizes the mean squared error (Kalman, 1960). The ability of the Kalman filters to estimate past, present, and even future states of a process made Kalman filters useful for optimizing cyclone track forecasts (Takeuchi, 1976a).

This optimization method, developed by Takeuchi (1976a, 1976b), does not in itself produce cyclone forecasts, but can enhance the forecast accuracy of existing statistical forecasting techniques. This method has been applied to the following three simple linear regression-based statistical forecasting techniques, producing an increase in forecast accuracy:

1. Statistical ForeCast model (SFC700 mbar) developed by Arakawa (1963)
2. Statistical and Numerical forecasting Technique (SNT) developed by the Japan Meteorological Agency, and
3. NHC72

As an example, the application of this optimization method enhanced the forecast accuracy of the NHC72 technique by 10% for 12- and 24-hour forecasts and increased the forecast accuracy of the SNT technique by 20% for 24-hour forecasts (Takeuchi, 1976b).

Beside optimization of other cyclone forecasting techniques, Kalman filters have also been used in combination with state-space models to forecast cyclones in the North Atlantic basin (Bril, 1995). In his technique, Bril (1995) suggests a linear and quadratic trend structural time series model, together with a Kalman filter, to forecast hurricane track. This technique uses recent past motion of the hurricane and historical storms with similar paths as predictors and performs at the same level as HURRAN and CLIPER. Chen and Snyder (2007) and Majumdar et al. (2006) have also conducted related studies with the aim to improve cyclone track forecast accuracy using Kalman filters.

4 Dynamical and numerical cyclone forecasting techniques

Two different processes are involved in dynamical cyclone forecasting. Some techniques forecast the track of the tropical cyclone vortex using equations describing the physical forces affecting the cyclone. Others use the wind prognoses at different air pressure levels from global or regional models to find the suitable pressure level that best resembles the motion of the cyclone vortex, similar to steering airflow determination techniques (Jeffries et al., 1993).

These techniques approximate the physical behavior of the atmosphere through numerical approximation of mathematical equations which describe the dynamics of weather systems and the physical forces behind cyclone formation and development (Elsberry, 1995; Jeffries et al., 1993). For this reason, they are called numerical. As these techniques work by modeling the different environmental forces affecting the cyclone, they are not dependent on the climatological data of the basin. This distinctive feature enables these techniques to perform in situations when suitable climatological data from the given basin are scarce (Jeffries et al., 1993).

Common to these techniques is that they approximate a combination of equations that describe the fluid dynamics and thermodynamics of the atmosphere (Gates et al., 1955; Holland, 2009; Hubert, 1957; Radford, 1994). These equations can be:

1. Mathematical equations that describe the large-scale horizontal motion of the atmosphere (Hubert, 1957; DeMaria, 1985).
2. Shallow-water equations (as the hydrodynamics of shallow water behave similarly to the dynamics of the atmosphere under the influence of the coriolis force).
3. Barotropic equations. These equations have been developed with the assumption that atmospheric structure does not vary with height. In this sense these models are single layered models and are therefore relatively simple to calculate.
4. Primitive equations. Here, primitive equations are used to represent a set of nonlinear differential equation—mainly the conservation of momentum, the thermal energy and the conservation of mass (continuity equation) to approximate the dynamic, thermodynamic and static state of the atmosphere (Jeffries et al., 1993).
5. Baroclinic equations. These equations have been formulated with the assumption that winds can change with height. In this sense these models take multiple atmospheric layers into account during calculation. These models are superior to the barotropic models as they can better capture the atmospheric structure and vertical wind variations.

These equations are often exceedingly complex and cannot be calculated directly. Instead, they are approximated through stepwise calculations described in numerical models. These numerical models tend to be sensitive to inaccurate initialization values, for example due to limitations in observational data. With inaccurate initial values, numerical models can rapidly diverge from the true values due to accumulation of error during the stepwise numerical approximation. Reliable forecasting from numerical models therefore requires correct initial data (position, intensity, and movement of the cyclone, as well as a long range of other variables). The main advantage of these models is that they can take into account the present and future synoptic structure of the atmosphere, and as a result these techniques perform well in situations where climatological information is not available. The main disadvantage of these models is that they are sensitive to insufficient or erroneous data and may produce inaccurate forecasts even for short-term forecast periods (Jeffries et al., 1993).

The essential elements of numerical models are (Haltiner and Williams, 1980; Holland, 2009; Leslie and Holland, 1995; Vanderman, 1962; Wang, 1998; Radford, 1994):

1. A grid of points that will hold the atmospheric parameters.
2. A series of polynomials or spectral functions that approximate the atmospheric fields.
3. Numerical representation of one or more vertically separate atmospheric layers or pressure levels.
4. An analysis/assimilation cycle which will obtain the initial values.
5. A means of bogussing⁹ to provide additional information in data-scarce regions.
6. A method for carrying the model equations forward in time.

⁹ During cyclone forecasting very often one faces situations where data coverage is poor. In order to compensate for the lack of data, bogus or fake observations are introduced into the model. This adding of bogus information is called bogussing.

7. Some form of physical parameterization to incorporate the effects of smaller variations within the atmosphere.
8. A means for handling large variations in the model variables along the boundaries.

To produce forecasts, numerical models employ computationally intensive calculations of a large number of atmospheric parameters collected from multiple vertically arranged pressure levels over a wide area which could range from a single cyclone formation basin up to the whole world. Hence, these techniques cannot be run on desktop PCs; instead, multi-processor computers capable of parallel processing are needed to run forecasts in these models (Lee and Liu, 2004, Neumann, 1985).

4.1 Barotropic forecasting techniques

Cyclones are highly influenced by the surrounding airflow which can be captured in a barotropic framework, but the movement of the cyclone is also modified by the coriolis force and the horizontal vorticity gradient of the surrounding air. Due to vertical wind shear and latent heat release that accompanies a cyclone, the cyclone will tend to move toward an area with maximum potential vorticity. This movement is mainly driven by two processes (Chan, 2005):

1. Advection, that is, transfer of atmospheric structures by the horizontal movement of an air mass. Advection depends on the structure and the speed of flow of the vortex and the surrounding air.
2. Heating that arises from a combination of latent heat release accompanying the cyclone when water vapor condenses in the surrounding atmosphere, and a very low vertical wind shear that is insufficient to disturb the heating process (Jeffries and Miller, 1993).

These techniques assume that the structure of the atmosphere does not change with height. In other words, these techniques regard the atmosphere as if it consisted of a single layer, which renders calculations in barotropic techniques simpler than in baroclinic techniques (see section 4.2). Several barotropic techniques are in operation at different meteorological stations. All the models follow the basic barotropic framework (Chan, 2005) with small modifications. These modifications are aimed to enhance the accuracy of the forecasts.

4.1.1 Sanders Barotropic

SANders BARotropic (SANBAR) technique was developed by Sanders and Burpee (1968) with an updated version of the technique published by Sanders et al. (1975). This technique uses barotropic equations for forecasting cyclone track and considers the cyclone positioned within a vertically averaged wind field. SANBAR is easy to construct and operate but cannot adequately handle the dynamics and synoptic structure of the atmosphere. This technique has been used by the NHC for a number of years. However, in 1990 SANBAR was replaced with VICBAR (Vic Ooyama BARotropic model) at NHC. VICBAR uses shallow-water equations for cyclone motion forecast and a Mercator projection as geographic grid (Demaria et al., 1992). For 12-hour forecasts, the average forecast error produced by SANBAR was around 102 kilometers. For 24-, 48-, and 72-hour forecasts the forecast errors were around 215, 463, and 741 kilometers, respectively (Figure 8).

Figure 8: Track forecast error produced by SANBAR for 12, 24, 48, and 72 hours in the North Atlantic basin. Corresponding average forecast errors are also shown using continuous grey lines

4.1.2 The Beta and Advection Model

The Beta and Advection Model (BAM) (Marks, 1992) produces forecasts using vertically-averaged horizontal wind predictions from the U.S. National Meteorological Center (NMC) spectral model, also taking into account variations of the coriolis force with latitude (Holland, 1983). Three forms of the BAM model, BAND (BAM Deep, 850-200 mbar), BAMB (BAM Medium, 850-400 mbar) and BAMS (BAM Shallow, 850-700 mbar) consider winds from different pressure layers at different altitudes (Simpson, 2003). Fnmoc Beta and Advection Model (FBAM) is a further adaptation of the BMA model, used by JTWC. In addition to the above, FBAM also takes into account the difference between the calculated steering current and the 12 hour old storm motion characteristics to forecast changes in the cyclone's motion (Dillon and Andrews, 1997). In the North Atlantic basin BAND and BAMB performs slightly better than BAMS (Figure 9a, b, and c). The reason could be that BAMS averages winds from fewer pressure layers and from lower altitudes than BAND and BAMB. The performance of the Beta and Advection Model is poor in the Northwest Pacific basin compared to the performance of Beta and Advection Models in the North Atlantic basin (Figure 9d).

Figure 9: Performance comparison of the three different versions of beta and advection models in the North Atlantic basin (a, b, and c) and d. Performance of the JTWC version of beta and advection model in the Southwest Pacific ocean

4.1.3 Multigrid Barotropic Model

The numerical Multigrid Barotropic technique (MUDBAR) is based on equations describing the large-scale horizontal motion of the atmosphere and uses an adaptive multi-grid method (superimposing nested uniform grids with varying mesh size to adapt the resolution and use a finer mesh around the moving vortex (Fulton, 2001). Vigh et al. (2003) compared the performance of the Multigrid Barotropic (MUDBAR) model with the Limited-Areas Sine Transform Barotropic model (LBAR) and found that MUDBAR provides similar accuracy as LBAR. The main differences between these models are the gridding process and the equations used to approximate the physical behavior of the atmosphere. While MUDBAR employs adaptive multiple grids based on a Mercator projection (Fulton, 1997), LBAR uses a single grid based on a Galerkin projection. Moreover, MUDBAR is based on barotropic equations, while LBAR is based on shallow-water equations. Last but not least, MUDBAR requires a fairly low amount of computational resources compared to LBAR (about a factor of 70 less resources) and can produce forecasts with similar accuracy as LBAR. It may be interesting to know that LBAR was developed as a portable alternative to VICBAR (Vigh et al., 2003; Horsfall et al., 1997), which entails that the same relationships in terms of computational resource demand and forecast accuracy apply between MUDBAR and VICBAR as between MUDBAR and LBAR; for example, MUDBAR will require less computational resources than VICBAR and will produce similarly accurate forecasts.

In addition to the commonly used barotropic models described above, Smith and Ulrich (1990) and Ulrich and Smith (1991) used a barotropic model to forecast the motion of both initially symmetric and asymmetric vortices. Though previous research established the relationship between tropical cyclone motion vectors and mean steering flow vectors (Brand et al., 1981; George and Gray, 1976), this relationship was not fully understood at that time (see section 3.4). Smith and Ulrich (1990) and Ulrich and Smith (1991) further examined the evolution of the vorticity and vorticity tendency fields and their impact on cyclone motion. Smith and Ulrich's work is unique by choosing to use different profiles for initial symmetric vortices than Chan and Williams (1987) and Fiorino and Elsberry (1989), and by using the method of Kasahara and Platzman (1963) to partition the vortex from the surrounding environment. Chan and Li (2005) and Cheung and Chan (1999a, 1999b) have conducted a detailed study on ensemble forecasting of tropical cyclones using their own version of a barotropic model.

4.2 Baroclinic cyclone forecasting techniques

Baroclinic cyclone forecasting techniques belong to dynamical forecasting. These techniques can be seen as enhanced barotropic techniques, as baroclinic techniques take into account changes in wind characteristics across vertical atmospheric layers. Hence, these techniques use several vertically arranged horizontal levels during analysis and forecasting. Baroclinic techniques are able to represent the atmospheric structure in greater detail and with higher temporal accuracy than barotropic techniques, as they take into account instantaneous changes of the wind fields. Moreover, as these techniques are based on multiple levels, vertical variations in wind, air temperature, and air pressure can also be included into the forecast (Jeffries et al., 1993).

4.2.1 Movable Fine Mesh

In the early 1970's a series of storms with irregular motion characteristics led to the development of statistical-dynamical models, which could better capture the irregular motion of the cyclones.

These irregular motion characteristics of cyclones eventually led to the development of the Movable Fine Mesh technique (MFM) (Hovermale and Livezey, 1977). Although the basis of this technique is comprised of the standard set of equations, the use of a moveable grid (ability of the grid to follow the storms as they are moving over time) and good horizontal and vertical resolution have made this technique unique (Kerlin, 1979). MFM uses primitive equations to produce cyclone forecasts. This technique was first built with ten vertical layers and 60 km horizontal grid spacing, but has subsequently gone through several modifications to enhance its forecasting capability. With a 3000 x 3000 km spatial coverage (using 50 x 50 grids) this model requires one and half hour to run on an *IBM 360/195* computer for producing a 48-hour forecast (Fiorino et al., 1982). MFM was first tested in the Atlantic basin in 1975. The average error produced by MFM for 12-hour forecast for cyclones between 1977 and 1987 was 120 kilometers. Like for other techniques, longer-term forecasts produced by this technique results in larger forecast errors (Figure 10).

Figure 10: Yearly and ten year average (from 1977 to 1987) forecast error produced by MFM for 12, 24, and 48 hours in the North Atlantic basin

4.2.2 The GFDL Multiply-Nested Moveable Mesh Hurricane Model

The GFDL Multiply-Nested Moveable Mesh Hurricane Model (GHM) is a baroclinic model and was developed for hurricane forecast by the National Oceanic and Atmospheric Administration, NOAA (Kurihara et al., 1998). GFDL contains 18 vertical atmospheric levels and uses a triply-nested grid configuration at each level (Elsberry, 1995; Simpson, 2003). The outer grid extends over a $75^\circ \times 75^\circ$ area with $1/2^\circ$ horizontal resolution (about 30 km), the middle grid extends over an $11^\circ \times 11^\circ$ area with $1/6^\circ$ horizontal resolution (about 15 km) and the inner grid extends over a $5^\circ \times 5^\circ$ area with $1/12^\circ$ horizontal resolution (about 9 km). The high resolution grids allow the GFDL model to resolve relatively small-scale features, such as eye and eye-wall, within a cyclone, but are not fully able to resolve highly complex features (Bender et al., 1993).

This model has been in operation since 1995 at NHC. After 1998, the model has been improved to reduce forecast error and to increase the computational efficiency of the model. The improvements include coupling the atmospheric component with the Princeton Ocean Model (POM) and increasing the vertical and horizontal resolution (Bender et al., 2007). In 2003 the vertical resolution was increased from 18 to 42 vertical levels and this change resulted in a considerable improvement in track forecast accuracy both for shorter and longer-term forecasts (Bender et al., 2007). Currently this model is run four times a day on Silicon Graphics supercomputers with 5248 Itanium processors.

4.2.3 The Navy Operational Atmospheric Prediction System

The navy operational atmospheric prediction system has two separate versions: one is for regional forecasts (known as Navy Operational Regional Atmospheric Prediction System) and the other is for global forecasts (Navy Operational Global Atmospheric Prediction System). During development, a *Control Data Corporation (CDC) CYBER 205* supercomputer was used to run these techniques. Using this computer the runtime for NOGAPS was 2 hours and for NORAPS 35-45 minutes depending on the region forecasted (Bayler and Lewit, 1992).

The Navy Operational Regional Atmospheric Prediction System (NORAPS) is a regional atmospheric prediction system. The forecast grid used in NORAPS is globally repositionable using either a Mercator, Lambert conformal or a polar stereographic projection and the grids can be set to any size and resolution (Fiorino et al., 1993; Hodur, 1982). In the western Pacific and western Atlantic, NORAPS is run with a horizontal resolution of 100 km, in the Mediterranean Sea with a resolution of 80 km and in the Middle East with a horizontal resolution of 40 km. NORAPS integrates 21 vertical levels and uses primitive equations to produce forecasts (Jeffries et al., 1993; Bayler and Lewit, 1992). This technique is run four times a day using u and v wind components, temperature, geopotential heights, mixing ratio (water vapor mass per kilogram of dry air), sea surface temperature and air surface pressure as input (Hodur, 1982). In January 1981 NORAPS was operationally used over the Mediterranean and performed better than the Fleet Numerical Oceanographic Center (FNOC) technique for 12-48-hour forecasts (Hodur, 1982).

The Navy Operational Global Atmospheric Prediction System (NOGAPS) technique was not designed particularly to forecast tropical cyclones. It is a global atmospheric prediction system used by the US Navy (Bayler and Lewit, 1992). This technique uses primitive equations with hydrostatic approximation to produce forecast, integrates 42 vertical levels and has a horizontal resolution of 55 kilometers (Chan and Kepert, 2010). This technique produces cyclone forecasts based on wind speed and direction, divergence of the atmosphere, ground and upper atmospheric temperature, humidity, surface pressure, ground wetness, and cloud patterns. Like for NORAPS, forecasts using this technique are run four times per day. One of the difficulties with NOGAPS is that the early parts of the track may be inconsistent with the recent motion of the cyclone and this initial discrepancy can cause an error in the forecasted track. A statistical post-processing technique developed by Elsberry et al. (1999) can be used to minimize this error. In addition, satellite-derived wind information can also be used to improve the performance of NOGAPS (Velden et al., 1998; Goerss et al., 1998). For 48- and 72-hour forecasts, NOGAPS performs better than GFDL but for shorter-term forecasts (12 and 24 hours) GFDL performs better than NOGAPS (Figure 11a). Moreover, the performance of NOGAPS is uneven in different cyclone formation basins (Figure 11b).

Figure 11: a. Performance comparison of GFDL and NOGAPS in the North Atlantic basin for 12, 24, 48, and 72 hours and b. Performance of NOGAPS in the North Atlantic, Northwest Pacific, and North Indian basin

4.2.4 One-way influence Tropical Cyclone Model

The One-way influence Tropical Cyclone Model (OTCM) is a three layered, coarse resolution (205 kilometer grid) model that covers an area of 6400 x 4700 kilometers and uses primitive equations to produce forecasts (Jeffries et al., 1993; Hodur and Buurk, 1978). 6 or 12 hour prognostic fields from the latest NOGAPS run are used to initialize this model. Though this model includes three vertical layers (1000-700, 700-400 and 400-100 mbar), emphasis is placed on the vortex movement in the lowest layer (effectively 850 mbar) (Jeffries et al., 1993). OTCM is used by JTWC to forecast cyclone track in the Northwest Pacific and North Indian basins, but has successfully been used also in the Southwest Pacific and Southeast Indian Ocean. Average forecast errors produced by this technique in the Northwest Pacific basin for cyclones between the years 1982 and 1996 were 232, 426, and 643 km for 24-, 48-, and 72-hour forecasts (Figure 12).

Figure 12: Yearly and 14 year average (1982-1996) forecast error produced by OTCM in the Northwest Pacific basin for 24, 48, and 72 hours

4.2.5 Global Forecast System

The Global Forecast System (GFS) is a primitive-equation-based baroclinic model (Kanamitsu, 1989). The earlier version of this model was known as global spectral Medium Range Forecast (MRF) model and was developed by Sela (1980). During development, the main emphasis was on producing forecasts for aviation worldwide (focusing on winds, temperature, surface pressure, humidity and precipitation). Nowadays GFS is additionally being used for cyclone track and intensity forecasting. Many modifications and improvements have been made to the model since it became operational in 1985 (Bonner et al., 1986; Bonner, 1988; Bonner, 1989). Currently, GFS includes 64 vertical levels and produces short- and long-term forecasts. Higher resolution (382 triangular waves¹⁰) is used to produce forecasts for up to 7 days ahead, while a lower resolution (190 triangular waves) is used to produce forecast for up to 16 days ahead. This model is run four times a day on an IBM RS/6000 (class viii) machine. This supercomputer takes about 12 minutes to produce forecasts for one day (Environmental Modeling Center, 2003) and all the outputs from this model are freely available over the internet.

4.2.6 Quasi-Lagrangian Model

The Quasi-Lagrangian Model (QLM) is a multilevel baroclinic model which uses primitive equations to produce cyclone track forecasts (Mathur, 1988; Mathur, 1991). Analysis and the lateral boundary conditions are initialized using the output of a global model. QLM integrates 16 vertical atmospheric levels and has a horizontal resolution of 40 km and 111 x 111 grid points (Prasad and Rama Rao, 2003). The physical processes that are incorporated into this model include surface friction effects, sea-air exchange of heat, convective release of heat, horizontal diffusion, and isobaric condition of water vapor (Prasad and Rama Rao, 2003). As the area covered by the grids is large (4400 km x 4400 km), the grids do not follow the cyclone. QLM was in use at NHC for a number of years. Between 1988 and 1994, the average forecast error produced by this technique for 12-hour forecasts was 105 kilometers. This performance was poor compared to CLIPER. However, for longer-time forecasts (24, 36, 48, and 72 hour), this model performed better than CLIPER (Figure 13). Currently QLM is in use at the India Meteorological Department and is run twice a day on a computer having a processing power of 14.4 teraflops (WMO, 2010).

Figure 13: Performance of QLM compared to CLIPER in the North Atlantic basin during the period 1988 to 1994

¹⁰ This resolution is comparable to a grid point model having a grid spacing of 37 kilometers.

4.2.7 Japanese Typhoon Model

The Japanese Typhoon Model (JTYM) is a limited area grid point model. The technique is similar to other baroclinic techniques, and has the following specifications (Jeffries et al., 1993):

1. Horizontal resolution is 50 km
2. 8 vertical levels are used
3. JTYM has 109 x 109 grid points (covers an area of approximately 5500 x 5500 km)
4. It uses two projection systems. If the latitude of the storm is greater than 20°N then a Lambert conformal projection is used. If the latitude is 0° to 20°N then a Mercator projection is used. In this way, geometric distortions of the grid (as compared to reality) are avoided.
5. Boundary conditions are updated once a day on the basis of the Japanese global spectral model
6. The model can provide up to 60-hour forecasts

After development, this technique has gone through several modifications. All the newer versions were characterized by better horizontal and vertical resolution. The Typhoon model that is in operation today has 20 km horizontal resolution, 30 vertical levels, 325 x 325 grid points and is run four times a day (Mino and Nagata, 2001).

In addition to the above mentioned baroclinic techniques that are widely used for cyclone track forecast there are some other multi-level techniques which were developed to forecast atmospheric variables in general, but can also be used for cyclone track and intensity forecast. Examples of this type of baroclinic techniques include:

- 1) The Global Environmental Multiscale model (GEM), developed and used by the Canadian meteorological center (Côté, Desmarais, et al., 1998; Côté, Gravel, et al., 1998; Yeh et al., 2002)
- 2) The United Kingdom Meteorological office Unified Model (MetUM), developed and used by the UK meteorological office (Lean et al., 2008; Lorenc et al., 2000)
- 3) The European Centre for Medium-Range Weather Forecasts (ECMWF) model developed and used by ECMWF (Roeckner et al., 1996), and
- 4) The ETA model, developed by Mesinger and Janjic (1974) and used by NMC is a regional model. ETA was improved in 1994 by NMC (Black, 1994) by increasing vertical and horizontal resolution. In 2006, ETA was fundamentally modified by the U. S. National Center for Environmental Prediction (NCEP) and renamed as the North American Mesoscale (NAM) model (NCEP, 2010)

5 Statistical-dynamical techniques

Before the 1970's the then available cyclone forecasting techniques were not able to forecast cyclone track with acceptable accuracy when the cyclone exhibited complex motion characteristics, e.g. recurving that is, a sudden change of direction. This shortcoming of the then existing techniques led to the development of statistical-dynamical techniques in the beginning of the 1970's. Statistical dynamical techniques use statistical screening of past storms to determine if they should be chosen as predictors. Statistical forecasts using these predictors are then combined with forecasts produced by a dynamical technique to produce the final forecast (Neumann, 1979a). As dynamical techniques work by modeling different environmental forces affecting the cyclone, these models are good at accounting for any atmospheric affects that can influence the cyclone's track. Statistical techniques in contrast are good at taking into account

the climatological behaviors of cyclones. The main logic behind the development of statistical-dynamical techniques was to combine the strengths of these two groups of techniques. Veigas (1966) was first to try a combination of statistical and dynamical techniques for cyclone forecasting, but this first attempt was not quite successful due to lack of barotropic data¹¹ from the tropical region. This line of work was later continued and Neumann and Lawrence (1975) achieved more success by increasing cyclone forecasting accuracy for recurving cyclones using statistical-dynamical techniques. This technique is known as NHC73 and is used by the NHC.

Statistical-dynamical techniques integrate outputs both from statistical and dynamical techniques. So the computational resources required by a certain statistical-dynamical technique depend on which statistical and dynamical techniques are being integrated.

5.1 National hurricane center statistical-dynamical technique series

The NHC statistical-dynamical techniques consist of a series of four statistical-dynamical techniques, starting with NHC73. Each successive technique (NHC83, NHC90, and NHC98) can be considered as a modified version of the previous one and these modifications have enabled each successor to perform better in forecasting cyclone track (Figure 14).

NHC73 relies on three different sub-systems to produce forecasts (Neumann and Lawrence, 1975):

Sub-system 1: Forecast from CLIPER (Neumann, 1972).

Sub-system 2: Forecast from steering methods using 1000, 700, and 500 mbar geopotential heights as steering levels (Miller et al., 1968).

Sub-system 3: Forecast from synoptic techniques, where 24, 36, and 48 hour geopotential-height prognoses from the NMC primitive equation model are used (Shuman and Hovermale, 1968).

NHC83 was developed to remedy problems with *NHC73*. The earlier problems were attributed to too much dependency on the 500 mbar level, too coarse grid system and the fact that changes of map scale with latitude change was not adjusted for. Also, there was an over-dependency on initial motion vectors, as well as a lack of visual access to the analysis. In addition, the calculations required to produce a forecast took long-term and forecasts were therefore slow (Neumann, 1988).

NHC83 was developed to overcome these problems. The new improved method combines the results of five different sub-systems (Neumann, 1988):

Subsystem 1: Forecast from CLIPER (Neumann, 1972).

Subsystem 2: Track forecast based on observed geopotential heights. The deep layer mean geopotential height fields used to produce forecast are constructed through averaging ten standard levels (between 1000 and 100 mbar).

Subsystem 3: Track forecast based on numerically forecasted geopotential height data (from the same height levels as in sub-system 2).

Subsystem 4: This sub-system combines outputs from sub-systems 1 and 2 and produces track forecast.

¹¹ Wind pressure information

Subsystem 5: At this stage outputs from sub-system 1, 2 and 3 are combined into a final forecast.

NHC90 is a further update of the NHC83 technique. This statistical-dynamical technique was developed by Neumann and McAdie (1991). The basic structure of NHC90 is similar to NHC83. NHC90 relies on five different sub-systems like NHC83, but some inconsistencies that were present in NHC83 have been eliminated in this updated version:

1. 48- and 60-hour forecasted positions produced by NHC83 were inconsistent compared to other segments of the forecasted track. This problem occurred mainly due to inconsistent selection of predictors which has been corrected in NHC90 through the use of a more suitable set of predictors.
2. Forecasts in NHC83 were stratified according to the initial position of the cyclone (either the cyclone was located equator-ward or pole-ward from 25°N latitude). In NHC83 different forecasting methods were used for these two zones. The assumption behind this stratification scheme was that cyclones located in the south zone will move toward west. However all cyclones in this zone do not have these motion characteristics. NHC83 thus produced erroneous results for those cyclones which had deviant motion characteristics. This problem has been rectified in NHC90 by using a different stratification based on *both* the initial position of the cyclone *and* its direction of movement.
3. Geopotential height analyses over the years 1962 and 1981 were used to develop NHC83. Before 1975, geopotential height observations near the equator were not available. As a result, NHC83 was developed using a too small sample size of previous cyclones. As additional analyses over the years 1975 and 1988 were used to develop NHC90, it can produce more accurate forecasts than NHC83.
4. Although both NHC83 and NHC90 provide graphical output, the graphical output produced by NHC83 did not include the locations of predictors. In contrast, these locations are included in NHC90.

NHC98 was developed for the Atlantic basin, and is the latest in the series of statistical-dynamical cyclone track forecasting techniques developed by NHC. This model combines cyclone track forecasting from three other independent techniques (Simpson, 2003):

1. CLIPER
2. Global Forecast System (GFS) based on current deep layer mean geopotential heights
3. GFS based on forecasted deep-layer mean geopotential heights

Figure 14: Performance of National Hurricane Center's statistical-dynamical forecasting techniques a. NHC73, b. NHC83, c. NHC90, and d. NHC98

5.2 Colorado State University Model

The Colorado State University Model (CSUM) was developed based on the work of Matsumoto (1984) to predict slow and looping cyclones in the western North Pacific, the South China Sea and the North Indian Ocean basins. This model uses three sets of regression equations to generate 24-, 48- and 72-hour forecasts. This technique performs well during periods when the storm is in one of three synoptic patterns (fast, slow, or looping). In contrast, the technique is not so promising if the cyclone is in a transition phase between synoptic patterns (Matsumoto, 1984; Aldinger and Stapler, 1998; Xu and Gray, 1982). CSUM performed at a level similar to WPCLPR for 24- and 48-hour forecasts during the period 1984 to 2000 in the Northwest Pacific basin. For 72-hour forecasts WPCLPR performed better than CSUM (Figure 15).

Figure 15: Performance of CSUM compared to WPCLPR in the Northwest Pacific basin during the period 1984 to 2000 for 24, 48, and 72 hours

5.3 Joint Typhoon Warning Center 92

The Joint Typhoon Warning Center 92 (JTWC92) (Englebreton, 1992) was developed on the basis of the work of Charles J. Neumann (Neumann, 1988; Neumann and McAdie, 1991) for

cyclone forecasts in the Northwest Pacific Ocean. Like NHC83 and NHC90, this technique relies on five sub-systems to produce a forecast. JTWC92 uses output from WPCLPR and deep-layer mean geopotential height fields. These fields can either be observed, or be derived from the NOGAPS model. To avoid the inconsistencies of NHC83, all applicable NHC90 modifications have been included into JTWC92.

6 Hybrid forecasting techniques

These forecasting techniques combine the output from two or more other techniques using statistical methods. As different forecasting techniques are optimized to handle different atmospheric variables (which are used as predictors), when two or more other techniques are combined, the combined technique will be able to handle a broader set of predictors and will inherit the strengths of the techniques which have been combined. However, while one is combining the output from different forecasting techniques, one is also aggregating the weaknesses (deviations and errors) of each constituent technique (Jeffries et al., 1993; Chu, 1999b).

Half Persistence and Climatology (HPAC) combines the results from XTRP and CLIM to produce cyclone track forecast. Equal weights are assigned to both XTRP and CLIM when combining the output of these two constituent models. HPAC computes forecast positions through direct interpolation between the corresponding forecast positions of XTRP and CLIM (Jeffries et al., 1993).

Combined Confidence Weighted Forecast (CCWF) combines the results of select forecasting techniques (usually OTCM, CSUM and HPAC) to produce cyclone track forecast. The inverse of the covariance matrices computed from historical and real-time cross-track and along-track errors are used as weighting function when combining the results from the different techniques (Jeffries et al., 1993; Chu, 1999b).

Blended forecast (BLND) uses the average of six (OTCM, CSUM, FBMA, JT92, CLIP and HPAC) forecasting techniques to produce a blended forecast (Dillon and Andrews, 1997).

Weighted forecast (WGTD) uses the same six component techniques as BLND, but with fixed weights (OTCM 29%, CSUM 22%, FBMA 14%, JT92 14%, HPAC 14% and CLIP 7%) (Dillon and Andrews, 1997). These weights have been empirically determined on the basis of the technique's previous performance (Chu, 1999b).

Dynamic Average technique (DAVE) is another hybrid forecasting technique that uses the average of seven dynamic models (NOGAPS, EGRR, JTYM, JT92, FBMA, OTCM and CSUM) to forecast cyclone track (Dillon and Andrews, 1997).

7 Other cyclone forecasting techniques

In addition to the cyclone forecasting techniques mentioned above, there are several other techniques which cannot be easily grouped into any of the above categories. Pedro et al. (2005) have developed an intelligent decision support framework for cyclone forecasting. This framework integrates case-based reasoning and fuzzy multi-criteria decision making techniques to support the forecaster in deciding which historical data should be included in the subsequent forecast process. The model was fed with 10 years of historical cyclone observation data (formulated as a fuzzy multi-criteria decision making problem). From this framework,

forecasters can get the best fitted historical cyclones in terms of usefulness and similarity to the current cyclone.

Systematic Approach and Forecast Aid (SAFA) is a knowledge-based expert system module which is not a cyclone forecasting technique in itself. This module supports the forecasters with information management, visualization and proactive investigation of frequently occurring forecasting errors (Carr et al., 2001).

The Automated Tropical Cyclone Forecasting System (ATCF) developed by the Naval Research Laboratory (NRL) in Monterey (Sampson and Schrader, 2000) is a computer-based application that automates and optimizes the cyclone forecasting process. ATCF provides a set of tools to graphically display tropical cyclone tracks (both actual and forecasted), analyze synoptic information, provide guidance for selecting best forecasted tracks and generate warning messages (Miller et al., 1990). Several other systems have been developed with similar functionality, for example, the Typhoon Analysis and Forecast Integration System (TAFIS) developed by Central Weather Bureau (CWB) Taiwan (Lu, 2007) and the Tropical Cyclone Information Processing System (TIPS) developed by Hong Kong observatory (Li and Ng, 2007).

8 How long the various techniques have been in use

The various techniques described in this article have been extended and developed over the years; techniques that were in use previously have been combined with new ones. To give an overview of the lifespan of the different cyclone track forecasting techniques we have compiled a chart that indicates the year of introduction for each technique (Figure 16).

Figure 16: Operational lifetime of different cyclone forecasting techniques

9 Summary

Accurate cyclone track forecasting requires precise observational data of the current cyclone, as well as high quality historical data that reveal typical patterns in cyclone movement. The crucial factors for accurate track forecasts are well-informed selection of suitable analogues from the historical data, and correct identification of those variables within the selected data that affect the cyclone's track. Both of these processes can be supported by a powerful forecasting technique. The choice of forecasting technique has considerable significance for the accuracy of forecasting.

Persistence forecasting techniques are the simplest among the cyclone forecasting techniques, as they use only the current movement and recent past movement of the cyclone. All other types of data, such as observational data on similar cyclones in the past, are excluded from analysis. Persistence techniques can be used for short-term forecast but are not particularly good for long-term forecasts.

Climatology forecasting techniques consider the tracks and sometimes the speed of historical cyclones in the same ocean basin as the current cyclone, with the assumption that similar climatological forces have been affecting all these previous cyclones. These techniques are thus highly dependent on the availability of historical observational data. In climatology forecasting, forecasts are produced by relating historical data to the recently observed track and speed of the current cyclone. As no other factors are considered, any unusual behavior of the cyclone will pose a challenge for these techniques. Hence, although climatology forecasting techniques are an improvement over persistence techniques, they are not fully adequate for long-term forecasts.

Integration of climatology and persistence techniques can provide more accurate forecasts than the two techniques could do individually. Such combined techniques are used by most cyclone forecasting centers to produce 12-72-hour forecasts. Like for other techniques, short-term forecasts produced by this technique are more accurate than long-term forecasts. For example, the average forecast error for CLIPER between 1996 and 2002 was around 92 kilometers for 12-hour forecasts and around 648 kilometers for 72-hour forecasts in the northern Atlantic.

As synoptic techniques use geopotential height data, these techniques are better able to capture the atmospheric structure of the cyclonic system and are able to produce better forecasts than the climatology and persistence techniques. Today, these techniques are not commonly used for forecasting because they are not able to handle the anomalous motion of cyclones, such as recurving, with acceptable accuracy.

Dynamical models are based on numerical approximation of mathematical equations that model atmospheric forces and are therefore not so dependent on climatological analogues. Rather than being dependent on climatological data these models gather required information from the atmosphere. Technically, these models are highly advanced and can produce accurate forecasts so long as the underlying models can be initiated correctly. On the downside, these models are computation intensive and therefore have to be run on high-performance computers and require very accurate observational data from multiple sources to ensure high accuracy.

The disability of purely statistical forecasting techniques to handle cyclones with a complex track (recurving or looping) encouraged the development of statistical dynamical techniques.

These techniques can forecast cyclones with recurving or looping track with reasonable accuracy.

Empirical techniques may be an even better option, but these techniques are highly dependent on the skill of the forecaster. These techniques have revealed the possibility of using a single data source (in this case satellite images) for cyclone track and intensity forecasting and wind-component analysis.

There are several cyclone track forecasting techniques which only use satellite images as input. Since the beginning of 1970 there have been great advancements in satellite-image-based tropical cyclone forecasting. In particular, neural-network-based techniques use satellite images of the current and previous cyclones for cyclone track forecasting. As neural-network-based techniques can produce forecasts with acceptable accuracy, can be run on standard PCs and use widely available, inexpensive satellite images as input, they can be an excellent and inexpensive aid for forecasting cyclone track (see e.g. Kovordányi and Roy, 2009).

During the last decades remarkable improvements have been made in cyclone track forecasting. However, we still do not know what forces make a cyclone change its position, which forces determine the direction and speed of movement after the formation of cyclone. Similarly, although we know the conditions necessary for cyclone formation, the relative importance of these conditions is not clear. For this reason, the following issues need to be further investigated in future research:

1. Changes in the environmental parameters and their effects on cyclone formation and movement
2. How the changes in upper-ocean thermal structures, which feed the tropical cyclones with energy, affect cyclone formation, intensity and track
3. The relationship between large scale circulations—especially the quasi-biennial oscillation and El Niño-southern oscillation—and tropical cyclone climatology

References

- Aldinger, W. T., Stapler, W., 1998. 1998 Annual Tropical Cyclone Report. JTWC. Pearl Harbor, Hawaii.
- Ali, M. M., Kishtawal, C. M., Jain, S., 2007. Predicting cyclone tracks in the North Indian ocean: An artificial neural network approach. *Geophysical Res. Lett.*, 34(4)
- Annette, P., 1978. Cyclogue : Analogic prediction of the course of tropical cyclones by national meteorological analysis center. Tech. Rep. No. 28. Australia Bureau of Meteorology, Melbourne.
- Anthes, R. A., 1982. Tropical cyclones: Their evolution, structure and effects. American Meteor. Soc., Boston, Mass.
- Arakawa, H., 1963. Studies of statistical prediction of typhoons. National Hurricane Research Project Report No. 61. Weather Bureau, USDC.

- Arnault, J., Roux, F., 2011. Characteristics of African easterly waves associated with tropical cyclogenesis in the Cape Verde Islands region in July-August-September of 2004-2008. *Atmos. Res.*, 100(1), 61-82. doi:10.1016/j.atmosres.2010.12.028
- Bayler, G., Lewit, H., 1992. The navy operational global and regional atmospheric prediction systems at the fleet numerical oceanography center. *Wea. and Forecast*, 7(2), 273-279.
- Beer, T., Giannini, L., 1980. Tropical cyclone cloudbands. *J. of the Atm. Sci.*, 37, 1511-1520.
- Bell, G. J., 1962. Predicting the movement of tropical cyclones in the region of the China Sea. *International Seminar on Tropical Cyclones*, 18-31 January 1962, Tokyo, Japan. 195-198.
- Bender, M. A., Ginis, I., Tuleya, R., Thomas, B., Marchok, T., 2007. The operational GFDL coupled Hurricane–Ocean prediction system and a summary of its performance. *Mon. Wea. Rev.*, 135(12), 3965-3989.
- Bender, M. A., Ross, R. J., Tuleya, R. E., Kurihara, Y., 1993. Improvements in tropical cyclone track and intensity forecasts using the GFDL initialization system. *Mon. Wea. Rev.*, 121(7), 2046-2061.
- Black, T. L., 1994. The new NMC mesoscale eta model: Description and forecast examples. *Wea. and Forecast*, 9(2), 265-278.
- Bonner, W. D., 1989. NMC overview: Recent progress and future plans. *Wea. and Forecast*, 4(3), 275-285.
- Bonner, W. D., White, G. H., Tracton, M. S., Kousky, V. E., Cressman, G. P., 1986. Global analysis and prediction at NMC Washington. *Second International Conference on Southern Hemisphere Meteorology*, Wellington, New Zealand, December 1-5.
- Bonner, W. D., 1988. Recent progress and future plans for numerical weather prediction at NMC. *Eighth Conference on Numerical Weather Prediction*, Baltimore, Maryland, February 22-26.
- Brand, S., Buenafe, C. A., Hamilton, H. D., 1981. Comparison of tropical cyclone motion and environmental steering. *Mon. Wea. Rev.*, 109, 908.
- Bril, G., 1995. Forecasting hurricane tracks using the Kalman filter. *Environmetrics*, 6(1), 7-16.
- Carr, L. E., III, Elsberry, R. L., 1994. Systematic and integrated approach to tropical cyclone track forecasting part 1 . approach overview and description of meteorological basis. *Tech. Rep. No. NPS-MR-94-002*. Naval Postgraduate School, Monterey, CA 93943-5114, 273pp
- Carr, L. E., Elsberry, R. L., Peak, J. E., 2001. Beta test of the systematic approach expert system prototype as a tropical cyclone track forecasting aid. *Wea. and Forecast*, 16(3), 355-368.

- CRED (Centre for Research on the Epidemiology of Disasters), 2009. Disaster profiles. Accessed, May 20, 2010, from http://www.emdat.be/result-disaster-profiles?disgroup=natural&period=1900%242010&dis_type=Storm&Submit=Display+Disaster+Profile
- Chan, J. C. L., 2005. The physics of tropical cyclone motion. *Annu. Rev. of Fluid Mech*, 37(1), 99-128.
- Chan, J. C. L., Gray, W. M., 1982. Tropical cyclone movement and surrounding flow relationships. *Mon. Wea. Rev.*, 110(10), 1354-1374.
- Chan, J. C. L., Kepert, J. D. (Eds.), 2010. *Global Perspectives on Tropical Cyclones: From Science to Mitigation*. World Scientific, 55-91
- Chan, J. C. L., Li, K. K., 2005. Ensemble forecasting of tropical cyclone motion using a barotropic model. part III: Combining perturbations of the environment and the vortex. *Meteorology and Atmospheric Physics*, 90(1), 109-126.
- Chan, J. C. L., Williams, R. T., 1987. Analytical and numerical studies of the beta-effect in tropical cyclone motion. I: Zero mean flow. *J. Atmos. Sci.*, 44(9), 1257–1265.
- Chen, J. M., Elsberry, R. L., Boothe, M. A., Carr, L. E., 1999. A simple statistical-synoptic track prediction technique for western North Pacific tropical cyclones. *Mon. Wea. Rev.*, 127(1), 89-102.
- Chen, Y., Snyder, C., 2007. Assimilating vortex position with an ensemble kalman filter. *Mon. Wea. Rev.*, 135(5), 1828-1845.
- Cheung, K. K. W., Chan, J. C. L., 1999a. Ensemble forecasting of tropical cyclone motion using a barotropic model. part II: Perturbations of the vortex. *Mon. Wea. Rev.*, 127(11), 2617-2640.
- Cheung, K. K. W., Chan, J. C. L., 1999b. Ensemble forecasting of tropical cyclone motion using a barotropic model. part I: Perturbations of the environment. *Mon. Wea. Rev.*, 127(6), 1229-1243.
- Chin, P. C., 1965. Survey of objective methods used in hong kong for predicting typhoon movement. *Inter-Regional Seminar on Advanced Tropical Meteorology*, pp1-14. Manila, Philippines.
- Chin, P. C., 1957. A climatological study of tropical cyclones over the china seas. *Proceedings of the Ninth Pacific Science Congress*. Bangkok, Thailand, pp 92-98.
- Chu, J. H. E., 1999a. Multi-basin tropical cyclone forecasting procedures. Accessed, June 25, 2010, from http://www.nrlmry.navy.mil/port_studies/Forecaster_Handbooks.BAK.23DEC09/_notes/TC_Forecasters_Guide/chap1/se103.htm

- Chu, J. H. E., 1999b. Numerical track forecast guidance. Accessed, June 28, 2010, from <http://www.nrlmry.navy.mil/~chu/chap5/se000.htm>
- Côté, J., Desmarais, J. G., Gravel, S., Méthot, A., Patoine, A., Roch, M., Staniforth, A., 1998. The operational CMC-MRB global environmental multiscale (GEM) model. Part II: Results. *Mon. Wea. Rev.*, 126(6), 1397–1418.
- Côté, J., Gravel, S., Méthot, A., Patoine, A., Roch, M., Staniforth, A., 1998. The operational CMC-MRB global environmental multiscale (GEM) model. Part I: Design considerations and formulation. *Mon. Wea. Rev.*, 126(6), 1373–1395.
- Debsarma, S. K., 2001. Cyclone and its warning system in Bangladesh. National Disaster Reduction Day, Dhaka, Bangladesh.
- Debsarma, S. K., 2009. Simulations of Storm Surges in the Bay of Bengal. *Marine Geodesy*, 32(2), 178–198.
- DeMaria, M., 1985. Tropical cyclone motion in a nondivergent barotropic model. *Mon. Wea. Rev.*, 113(7), 1199–1210.
- Demaria, M., Aberson, S. D., Ooyama, K. V., Lord, S. J., 1992. A nested spectral model for hurricane track forecasting. *Mon. Wea. Rev.*, 120(8), 1628–1643.
- DeMaria, M., Knaff, J. A., Connell, B. H., 2001. A tropical cyclone genesis parameter for the tropical Atlantic. *Weather and Forecasting*, 16(2), 219–233.
- Dillon, C. P., Andrews, M. J., 1997. 1997 annual tropical cyclone report. Pearl Harbour, Hawaii: JTWC.
- Dong, K., Neumann, C. J., 1986. The relationship between tropical cyclone motion and environmental geostrophic flows. *Mon. Wea. Rev.*, 114(1), 115–122.
- Dvorak, V. F., 1972. A technique for analysis and forecasting of tropical cyclone intensities from satellite image. NOAA Tech. Rep. No. NESS 36, 15pp.
- Dvorak, V. F., 1975. Tropical cyclone intensity analysis and forecasting from satellite imagery. *Mon. Wea. Rev.*, 103(5), 420–430.
- Dvorak, V. F., 1984. Tropical cyclone intensity analysis using satellite data. NOAA Tech. Rep. No. NESDIS 11, 47 pp.
- Elsberry, R. L., 1995. Recent advancements in dynamical tropical cyclone track predictions. *Meteorology and Atmospheric Physics*, 56(1-2), 81–99. doi:10.1007/BF01022522
- Elsberry, R. L., Boothe, M. A., Ulses, G. A., Harr, P. A., 1999. Statistical postprocessing of NOGAPS tropical cyclone track forecasts. *Mon. Wea. Rev.*, 127(8), 1912–1919.

- Elsner, J. B., Kara, A. B., 1999. Hurricanes of the North Atlantic: climate and society. Oxford University Press.
- Elsner, J. B., Niu, X., Jagger, T. H., 2004. Detecting shifts in hurricane rates using a Markov chain Monte Carlo approach. *J. of Climate*, 17(13), 2652-2666.
- Emanuel, K., 2007. Environmental factors affecting tropical cyclone power dissipation. *Journal of Climate*, 20(22), 5497–5509.
- Englebreton, R. E., 1992. Final report for the joint typhoon warning center JTWC92 model. Tech. Rep. No. A646852. Monterey, CA., Science Applications International Corporation, 98pp.
- Environmental Modeling Center., 2003. The GFS Atmospheric Model (p. 14). EMC, Camp Springs, Maryland.
- Feng, B., Liu, J. N. K., 2004. SEMO-MAMO, a 3-phase module to compare tropical cyclone satellite images using a modified Hausdorff distance. *Proceedings of the Third International Conference on Machine Learning and Cybernetics, Shanghai, China*, 3808-3813.
- Fett, R. W., Brand, S., 1975. Tropical cyclone movement forecasts based on observations from satellites. *J. of Appl. Meteorol*, 14(4), 452-465.
- Fiorino, M., Elsberry, R. L., 1989. Some aspects of vortex structure related to tropical cyclone motion. *J. of the Atm. Sci*, 46(7), 975-990.
- Fiorino, M., Goerss, J. S., Jensen, J. J., Harrison, E. J., 1993. An Evaluation of the real-time tropical cyclone forecast skill of the navy operational global atmospheric prediction system in the western north pacific (No. JA 431:006:92) (p. 22). NRL, Monterey, CA.
- Fitzpatrick, P. J., 2006. Hurricanes: a reference handbook. ABC-CLIO.
- Fraedrich, K., Raible, C. C., Sielmann, F., 2003. Analog ensemble forecasts of tropical cyclone tracks in the australian region. *Wea. and Forecast*, 11(1), 3-11.
- Fraedrich, K., Rückert, B., 1998. Metric adaption for analog forecasting. *Physica A: Stat. Mech. and its Applications*, 253(1-4), 379-393.
- Fiorino, M., Harrison, E. J., Marks, D. G., 1982. A Comparison of the Performance of Two Operational Dynamic Tropical Cyclone Models. *Monthly Weather Review*, 110, 651.
- Fulton, S. R., 1997. A comparison of multilevel adaptive methods for hurricane track prediction. *Electro. Transactions on Numer. Anal*, 6, 120-132.
- Fulton, S. R., 2001. An adaptive multigrid barotropic tropical cyclone track model. *Mon. Wea. Rev*, 129(1), 138-151.

- Gates, W. L., Pocinki, L. S., Jenkins, C. F., 1955. Results of numerical forecasting with the barotropic and thermotropic atmospheric models. Geophysical Research Paper No. AD0101943. Airforce Cambridge Research Labs, Bedford MA.
- Gentry, R. C., 1963. Forecasting the movement of tropical cyclones, A survey. Symposium on Tropical Meteorology, Rotorua, New Zealand.
- George, J. E., Gray, W. M., 1976. Tropical cyclone motion and surrounding parameter relationships. *J. of Appl. Meteorol*, 15(12), 1252-1264.
- Goerss, J., 2008. Impact of satellite observations on the tropical cyclone track forecasts of the navy operational global atmospheric prediction system. *Mon. Wea. Rev*, 137(1), 41-50.
- Goerss, J. S., Hogan, T. F., 2006. Impact of satellite observations and forecast model improvements on tropical cyclone track forecasts. Naval Research Laboratory, Monterey, CA.
- Goerss, J. S., Velden, C. S., Hawkins, J. D., 1998. The impact of multispectral GOES-8 wind information on Atlantic tropical cyclone track forecasts in 1995. part II: NOGAPS forecasts. *Mon. Wea. Rev*, 126(5), 1219-1227.
- Gray, W. M., 1968. Global view of the origin of tropical disturbances and storms. *Monthly Weather Review*, 96(10), 669–700.
- Gray, W. M., 1979. Hurricanes: Their formation, structure and likely role in the tropical circulation. In *Meteorology Over Tropical Oceans* (pp. 155-218). Roy. Meteor. Soc.
- Gray, W. M., 1998. The formation of tropical cyclones. *Meteorology and Atmospheric Physics*, 67(1-4), 37-69. doi:10.1007/BF01277501
- Guard, C. P., 1992. 1992 annual tropical cyclone report. Pearl Harbor, Hawaii: JWTC.
- Haltiner, G. J., Williams, R. T., 1980. Numerical prediction and dynamic meteorology, second ed. Wiley, New York.
- Hodur, R. M., 1982. Description and evaluation of NORAPS: The navy operational regional atmospheric prediction system. *Mon. Wea. Rev*, 110(11), 1591-1602.
- Hodur, R. M., Buurk, S. D., 1978. The fleet numerical weather central tropical cyclone model: Comparison of cyclic and one-way interactive boundary conditions. *Mon. Wea. Rev*, 106(12), 1665-1671.
- Holland, G. J., 1980. An analytic model of the wind and pressure profiles in hurricanes. *Mon. Wea. Rev*, 108(8), 1212-1218.

- Holland, G. J., 1983. Tropical cyclone motion: Environmental interaction plus a beta effect. *J. of the Atm. Sci.*, 40(2), 328-342.
- Holland, G. J., 2009. Global guide to tropical cyclone forecasting. Bureau of meteorology research center, Melbourne, Australia. Accessed, April 18, 2011, from http://cawcr.gov.au/publications/BMRC_archive/tcguide/global_guide_intro.htm
- Hope, J. R., Neumann, C. J., 1970. An operational technique for relating the movement of existing tropical cyclones to past tracks. *Mon. Wea. Rev.*, 98(12), 925-933.
- Hope, J. R., Neumann, C. J., 1977. A survey of world wide tropical cyclone prediction models. , Volume of Conference Papers, 11th Technical Conference on Hurricane and Tropical Meteorology, December 13-16, Published by Amer. Meteorol. Soc., Boston, 375-380.
- Horsfall, F., DeMaria, M., Gross, J. M., 1997. Optimal use of large-scale boundary and initial fields for limited-area hurricane forecast models. 22nd Conf. on Hurricanes and Tropical Meteorology, Fort Collins, CO, Amer. Meteorol. Soc. 571-572.
- Hovermale, J. B., Livezey, R. E., 1977. Three-year performance characteristics of the NMC hurricane model. Miami, FL. 122-125.
- Hubert, W. E., 1957. Hurricane trajectory forecasts from a non-divergent, non-geostrophic, barotropic model. *Mon. Wea. Rev.*, 85(3), 83-87.
- Isaksen, L., Stoffelen, A., 2000. ERS scatterometer wind data impact on ECMWF's tropical cyclone forecasts. *IEEE Trans. Geosci. Remote Sens.*, 38(4 II), 1885-1892.
- Jarrell, J. D., Somervell, W. L., 1970. A computer technique for using typhoon analogs as a forecast aid. Tech. Rep. No. A068800. Navy weather research facility Norfolk, VA.
- Jeffries, R. A., Miller, R. J., 1993. Tropical cyclone forecasters reference guide 3. tropical cyclone formation. Tech. Rep. No. NRL/PU/7515--93-0007. NRL, Monterey, CA 93943-5006.
- Jeffries, R. A., Sampson, C. R., Carr, L. E., Chu, J. H., 1993. Tropical cyclone forecasters reference guide. 5. numerical track forecast guidance. Tech. Rep. No. NRL/PU/7515--93-0011. NRL, Monterey, CA 20363-5100.
- Johnson, G. P., Lin, F. C., 1995. Hurricane tracking via backpropagation neural network. Proceedings of IEEE International Conference on Neural Networks, Perth, WA, Australia, 1103-1106.
- Kalman, R. E., 1960. A new approach to linear filtering and prediction problems. *Transaction of the ASME-Journal of basic Engineering*, 82(1), 35-45.
- Kanamitsu, M., 1989. Description of the NMC global data assimilation and forecast system. *Wea. and Forecast*, 4(3), 335-342.

- Kasahara, A., Platzman, G. W., 1963. Interaction of a hurricane with the steering flow and its effect upon the hurricane trajectory. *Tellus*, 15(4), 321–335.
- Keenan, T. D., 1985. Statistical forecasting of tropical cyclone movement in the Australian region. *Q. J. R. Meteorol. Soc.*, 111(468), 603–615.
- Keenan, T. D., 1982. A diagnostic study of tropical cyclone forecasting in Australia. *Aust. Meteorol. Mag.*, 30(1), 69–80.
- Kerlin, J., 1979. Performance test of the movable-area fine-mesh model in the western Pacific.
- Kidder, S. Q., Goldberg, M. D., Zehr, R. M., DeMaria, M., Purdom, J. F. W., Velden, C. S., 2000. Satellite analysis of tropical cyclones using the advanced microwave sounding unit (AMSU). *Bull. Am. Meteorol. Soc.*, 81(6), 1241–1259.
- Kokhanovsky, A. A., Hoyningen-Huene, W. V., 2004. Optical properties of a hurricane. *Atmos. Res.*, 69(3–4), 165–183. doi:10.1016/j.atmosres.2003.09.005
- Kovordányi, R., Roy, C., 2009. Cyclone track forecasting based on satellite images using artificial neural networks. *ISPRS J. of Photogrammetry and Remote Sens.*, 64(6), 513–521.
- Kurihara, Y., Tuleya, R. E., Bender, M. A., 1998. The GFDL hurricane prediction system and its performance in the 1995 hurricane season. *Mon. Wea. Rev.*, 126(5), 1306–1322.
- Lajoie, F. A., 1976. On the direction of movement of tropical cyclones. *Aust. Meteor. Mag.*, 24, 95–104.
- Lajoie, F. A., Nicholls, N., 1974. A relationship between the direction and movement of tropical cyclones and the structure of their cloud systems. Bureau of Meteorology Tech. Rep. No. 11. Melbourne, Australia, 22pp.
- Langland, R. H., Velden, C., Pauley, P. M., Berger, H., 2009. Impact of satellite-derived rapid-scan wind observations on numerical model forecasts of hurricane Katrina. *Mon. Wea. Rev.*, 137(5), 1615–1622.
- Le, M. J. F., Leslie, L. M., Bennett, A. F., 1996. Tropical cyclone Beti—an example of the benefits of assimilating hourly satellite wind data. *Aust. Meteorol. Mag.*, 45(4), 275–279.
- Le, M. J. F., Leslie, L. M., Spinoso, C., 1996. The impact of spatial and temporal distribution of satellite observations on tropical cyclone data assimilation: Preliminary results. *Meteorol. and Atm. Phys.*, 60(1–3), 157–163.
- Le, M. J. F., Smith, W. L., Callan, G. M., 1985. Hurricane Debby - an illustration of the complementary nature of VAS soundings and cloud and water vapor motion winds. *Bull. Am. Meteorol. Soc.*, 66(3), 258–263.

- Le, M. J., Leslie, L. M., Pescod, N., Spinoso, C., Morison, R., 1997. The importance of direct readout satellite data in sub-synoptic scale data assimilation and numerical weather prediction. *Advances in Space Research*, 19(3), 413-422.
- Lean, H. W., Clark, P. A., Dixon, M., Roberts, N. M., Fitch, A., Forbes, R., Halliwell, C., 2008. Characteristics of high-resolution versions of the Met Office Unified Model for forecasting convection over the United Kingdom. *Mon. Wea. Rev.*, 136(9), 3408–3424.
- Lee, R. S. T., Liu, J. N. K., 1999. An automatic satellite interpretation of tropical cyclone patterns using elastic graph dynamic link model. *Int. J. Pat. Recognit. Artif. Intell.*, 13(8), 1251-1270.
- Lee, R. S. T., Liu, J. N. K., 2000. Tropical cyclone identification and tracking system using integrated neural oscillatory elastic graph matching and hybrid RBF network track mining techniques. *IEEE Transactions on Neural Networks*, 11(3), 680-689.
- Lee, R. S. T., Liu, J. N. K., 2002. An automatic tropical cyclone pattern recognition and classification system using composite neural oscillatory-based EGDLM. *Journal of Fuzzy Systems*, 4(1), 616-625.
- Lee, R., Liu, J., 2004. iJADE WeatherMAN: A weather forecasting system using intelligent multiagent-based fuzzy neuro network. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, 34(3), 369-377.
- Leslie, L. M., Hess, G. D., Holland, G. J., Morison, R. P., Fraedrich, K., 1992. Predicting changes in intensity of tropical cyclones using a Markov chain technique. *Aust. Meteorol. Mag.*, 40(1), 41-46.
- Leslie, L. M., Holland, G. J., 1995. On the bogussing of tropical cyclones in numerical models: A comparison of vortex profiles. *Meteorol. and Atm. Phys.*, 56(1), 101-110.
- Leslie, L. M., LeMarshall, J. F., Morison, R. P., Spinoso, C., Purser, R. J., Pescod, N., Seecamp, R., 1998. Improved hurricane track forecasting from the continuous assimilation of high quality satellite wind data. *Mon. Wea. Rev.*, 126(5), 1248-1258.
- Li, S. W., Ng, P. W., 2007. The tropical cyclone information processing system (TIPS) of the Hong Kong observatory. Unpublished manuscript.
- Lorenc, A. C., Ballard, S. P., Bell, R. S., Ingleby, N. B., Andrews, P. L. F., Barker, D. M., Bray, J. R., Clayton, A. M., Dalby, T., Li, D., Payne, T. J., Saunders, F. W., 2000. The Met. Office global three-dimensional variational data assimilation scheme. *Q J Roy Meteor Soc.*, 126(570), 2991–3012.
- Lourensz, R. S., 1981. Tropical cyclone in the Australian region July 1909 to June 1980. P. O. Box 1289K, Melbourne, Australia, 94pp: Bureau of Meteorology.

- Lu, K.-C., 2007. Typhoon forecast and warning system in Taiwan: Proceedings 2nd International Conference on Urban Disaster Reduction. Taipei, Taiwan.
- Ma, L.-M., Tan, Z.-M., 2009. Improving the behavior of the cumulus parameterization for tropical cyclone prediction: Convection trigger. *Atmos. Res.*, 92(2), 190-211.
doi:10.1016/j.atmosres.2008.09.022
- Majumdar, S. J., Aberson, S. D., Bishop, C. H., Buizza, R., Peng, M. S., Reynolds, C. A., 2006. A comparison of adaptive observing guidance for Atlantic tropical cyclones. *Mon. Wea. Rev.*, 134(9), 2354-2372.
- Marks, D. G., 1992. The beta and advection model for hurricane track forecasting. NOAA Tech. Memo. NWS NMC 70. Camp Springs, Maryland, 89pp.
- Marshall, J. L., 1998. Cloud and water vapour motion vectors in tropical cyclone track forecasting - A review. *Meteorol. and Atm. Phys.*, 65(3), 141-151.
- Mathur, M. B., 1988. Development of the NMC's high resolution hurricane model. American Meteorological Society, 17th Conference on Hurricanes and Tropical Meteorology, Miami, Florida. 60-63.
- Mathur, M. B., 1991. The national meteorological center's quasi-Lagrangian model for hurricane prediction. *Mon. Wea. Rev.*, 119(6), 1419-1447.
- Matsumoto, C. R., 1984. A statistical method for one- to three-day tropical cyclone track prediction (doctoral thesis). Access no., ADA151605, Air Force Inst. of Tech., Wright-Patterson Air Force Base, OH.
- McBride, J. L., Holland, G. J., 1987. Tropical-cyclone forecasting: A worldwide summary of techniques and verification statistics. *Bull. Am. Meteorol. Soc.*, 68(10), 1230-1238.
- Mesinger, F., Janjic, Z. I., 1974. Noise due to time-dependent boundary conditions in limited area models. Rep. No. 4. Geneva: WMO.
- Miller, B. I., Chase, P. P., 1966. Prediction of hurricane motion by statistical methods. National Hurricane Research Laboratory, Environmental Science Service Administration, Miami, FL, 94(6), 399-406.
- Miller, B. I., Hill, E. C., Chase, P. P., 1968. A revised technique for forecasting hurricane movement by statistical methods. *Mon. Wea. Rev.*, 96(8), 540-548.
- Miller, B. I., Moore, P. L., 1960. A comparison of hurricane steering levels. *Bull. Amer. Meteor. Soc.*, 41, 59-63.
- Miller, R. G., 1958. Statistics and predictability of weather in "Studies in Statistical Weather Prediction". Final Rep., Contract AF 19(604)-1590. Travelers Weather Research Center.

- Miller, R., Schrader, A., Sampson, C., Tsui, T., 1990. The Automated Tropical Cyclone Forecasting System (ATCF). *Weather and forecasting*, 5, 653–660.
- Mino, H., Nagata, M., 2001. Outline of the new Typhoon prediction models at JMA (Technical review) (p. 13). Japan Meteorological Agency.
- NCEP., 2010. The north American mesoscale forecast system. Accessed, September 5, 2010, from <http://www.emc.ncep.noaa.gov/?branch=NAM>
- Neumann, C. J., 1972. An alternative to the HURRAN (hurricane analog) tropical cyclone forecast system. NOAA Technical Memorandum NWS SR-62. National Hurricane Center, Miami, Florida, 24pp.
- Neumann, C. J., 1979a. A guide to Atlantic and eastern Pacific models for the prediction of tropical cyclone motion. NOAA Technical Memorandum NWS No. 932. National Hurricane Center, Miami, Florida, 26pp.
- Neumann, C. J., 1979b. On the use of deep-layer-mean geopotential height fields in statistical prediction of tropical cyclone motion. 6th Conference on Probability and Statistics in Atmospheric Sciences. Amer. Meteorol. Soc., Boston. 32-38.
- Neumann, C. J., 1988. The national hurricane center NHC83 model. Tech. Rep. No. NWS NHC 41. National Hurricane Center, Coral Gables, FL, 47pp.
- Neumann, C. J., 1985. The Role of Statistical Models in the Prediction of Tropical Cyclone Motion. *The American Statistician*, 39(4), 347-357. doi:10.2307/2683013
- Neumann, C. J., Jarvinen, B. R., McAdie, C. J., Elms, J. D., 1993. Tropical cyclones of the North Atlantic Ocean, 1871-1992. National Oceanic and Atmospheric Administration, National Weather Service, National Environmental Satellite, Data, and Information Service, FL, 193pp.
- Neumann, C. J., Lawrence, M. B., 1975. An operational experiment in the statistical-dynamical prediction of tropical cyclone motion. *Mon. Wea. Rev.*, 103(8), 665-673.
- Neumann, C. J., Mandal, G. S., 1978. Statistical prediction of tropical storm motion over the Bay of Bengal and Arabian Sea. *Indian J. Meteor. Hydrol. and Geophys.*, 29, 487-500.
- Neumann, C. J., McAdie, C. J., 1991. A revised national hurricane center NHC83 model (NHC90). Tech. Rep. No. NWS NHC 44. National Hurricane Center, Coral Gables, FL, 37pp.
- Neumann, C. J., Pelissier, J. M., 1981. Models for the prediction of tropical cyclone motion over the North Atlantic: An operational evaluation. *Mon. Wea. Rev.*, 109(3), 522-538.
- Pedro, S. J., Burstein, F., Sharp, A., 2005. A case-based fuzzy multicriteria decision support model for tropical cyclone forecasting. *Eur. J. Oper. Res.*, 160(2), 308-324.

- Pickle, J., 1991. Forecasting short-term movement and intensification of tropical cyclones using pattern-recognition techniques. Environmental Research Paper No. ADA256705. Phillips Lab Hanscom AFB, MA.
- Prasad, K., Rama Rao, Y. V., 2003. Cyclone track prediction by a quasi-lagrangian limited area model. *Meteorol. and Atm. Phys.*, 83(3-4), 173-185.
- Radford, A. M., 1994. Forecasting the movement of tropical cyclones at the met. office. *Meteor. Appl.*, 1, 355-363.
- Renard, R. J., Colgan, S. G., Daley, M. J., Rinard, S. K., 1973. Forecasting the motion of north Atlantic tropical cyclones by the objective MOHATT scheme. *Mon. Wea. Rev.*, 101(3), 206-214.
- Riehl, H., Shafer, R. J., 1944. The recurvature of tropical storms. *J. Atmos. Sci.*, 1(1), 42-54.
- Roeckner, E., Arpe, K., Bengtsson, L., Christoph, M., Dumenil, L., Esch, M., Giorgetta, M., Schulzweida, U., Claussen, M., Schlese, U., 1996. The atmospheric general circulation model ECHAM-4: Model description and simulation of present-day climate (No. MPI-Report 218). Hamburg, Germany: Max Planck Institute for Meteorology.
- Sampson, C. R., Schrader, A. J., 2000. The automated tropical cyclone forecasting system (version 3.2). *Bull. Am. Meteorol. Soc.*, 81(6), 1231-1240.
- Sandeep, S., Chandrasekar, A., Singh, D., 2006. The impact of assimilation of AMSU data for the prediction of a tropical cyclone over India using a mesoscale model. *Int. J. Remote Sens.*, 27(20), 4621-4653.
- Sanders, F., Burpee, R. W., 1968. Experiments in barotropic hurricane track forecasting. *J. of Appl. Meteorol.*, 7(3), 313-323.
- Sanders, F., Pike, A. C., Gaertner, J. P., 1975. A barotropic model for operational prediction of tracks of tropical storms. *J. of Appl. Meteorol.*, 14(3), 265-280.
- Sauer, T., Yorke, J. A., Casdagli, M., 1991. Embedology. *J. of Stat. Phys.*, 65(3), 579-616.
- Sela, J. G., 1980. Spectral modeling at the national meteorological center. *Mon. Wea. Rev.*, 108, 1279-1292.
- Sharkov, E. A., 2000. Global tropical cyclogenesis. Springer.
- Sheets, R. C., 1990. The National Hurricane Center—Past, Present, and Future. *Weather and Forecasting*, 5, 185–232.
- Shuman, F. G., Hovermale, J. B., 1968. An operational six-layer primitive equation model. *J. of Appl. Meteorol.*, 7(4), 525-547.

- Sievers, O., Fraedrich, K., Raible, C. C., 2000. Self-adapting analog ensemble predictions of tropical cyclone tracks. *Wea. and Forecast*, 15(5), 623-629.
- Simpson, R. H., 2003. Hurricane!: coping with disaster : progress and challenges since Galveston, 1900. American Geophysical Union.
- Simpson, R. H., 1971. The decision process in hurricane forecasting (Technical No. NWS SR-63). NOAA Technical Memorandum (p. 35).
- Smith, K., Petley, D. N., 2009. Environmental hazards: assessing risk and reducing disaster. Taylor & Francis.
- Smith, R. K., Ulrich, W., 1990. A numerical study of tropical cyclone motion using a barotropic model. I: The role of vortex asymmetries. *Q. J. R. Meteorol. Soc*, 116(492), 337-362.
- Takeuchi, K., 1976a. Application of the Kalman filter to cyclone forecasting: 1. methodology, 2. typhoon forecasting. Rep. No. RM-76-9. International Institute for Applied Systems Analysis, Laxenburg, Austria.
- Takeuchi, K., 1976b. Application of the Kalman filter to cyclone forecasting: 3. hurricane forecasting, 4. additional typhoon forecasting. Rep. No. RM-76-62. International Institute for Applied Systems Analysis, Laxenburg, Austria.
- Tomassini, M., Lemeur, D., Saunders, R. W., 1998. Near-surface satellite wind observations of hurricanes and their impact on ECMWF model analyses and forecasts. *Mon. Wea. Rev*, 126(5), 1274-1286.
- Tse, S. Y. W., 1966. A new method for the prediction of typhoon movement using the 700 mb chart. *Q. J. R. Meteorol. Soc*, 92(392), 239-253.
- Tse, S. Y. W., 1970. Typhoon movement. The Regional Training Seminar, Singapore. Synoptic analysis and forecasting in the tropics of Asia and the Southwest Pacific. 158-171.
- Ulrich, W., Smith, R. K., 1991. A numerical study of tropical cyclone motion using a barotropic model. II: Motion in spatially-varying large-scale flows. *Q. J. R. Meteorol. Soc*, 117(497), 107-124.
- Vanderman, L. W., 1962. An improved NWP model for forecasting the paths of tropical cyclones. *Mon. Wea. Rev*, 90(1), 19-22.
- Veigas, K. W., 1966. The development of a statistical-physical hurricane prediction model. Final Report, U.S.W.B. Contract Cwb 10966, Travellers Weather Research Center, Hartford, CT, 19 pp.

- Veigas, K. W., Miller, R. G., Howe, G. M., 1959. Probabilistic prediction of hurricane movements by synoptic climatology. *Occasional Papers in Meteorology*, no. 2, the Travelers Weather Research Center, Inc., Hartford, Conn., pp. 54.
- Velden, C. S., Hayden, C. M., Paul, M. W., Franklin, J. L., Lynch, J. S., 1992. The impact of satellite-derived winds on numerical hurricane track forecasting. *Wea. and Forecast*, 7(1), 107-118.
- Velden, C. S., Olander, T. L., Wanzong, S., 1998. The impact of multispectral GOES-8 wind information on Atlantic tropical cyclone track forecasts in 1995. part I: Dataset methodology, description, and case analysis. *Mon. Wea. Rev.*, 126(5), 1202-1218.
- Vigh, J., Fulton, S. R., DeMaria, M., Schubert, W. H., 2003. Evaluation of a multigrid barotropic tropical cyclone track model. *Mon. Wea. Rev.*, 131(8), 1629-1636.
- Villmann, T., Merényi, E., Hammer, B., 2003. Neural maps in remote sensing image analysis. *Neural Networks*, 16(3-4), 389-403.
- Wang, D., Liang, X., Duan, Y., Chan, J. C. L., 2006. Impact of four-dimensional variational data assimilation of atmospheric motion vectors on tropical cyclone track forecasts. *Wea. and Forecast*, 21(4), 663-669.
- Wang, Y., Holland, G. J., 1996a. The beta drift of baroclinic vortices. part I: Adiabatic vortices. *J. Atm. Sci.*, 53(3), 411-427.
- Wang, Y., Holland, G. J., 1996b. The beta drift of baroclinic vortices. part II: Diabatic vortices. *J. Atm. Sci.*, 53(24), 3737-3756.
- Wang, Y., Holland, G. J., 1996c. Tropical cyclone motion and evolution in vertical shear. *J. Atm. Sci.*, 53(22), 3313-3332.
- Wang, Y., 1998. On the bogusing of tropical cyclones in numerical models: The influence of vertical structure. *Meteorol. and Atm. Phys.*, 65(3-4), 153-170.
- Wei, K., Jing, Z.-L., 2010. Spiral band model optimization by chaos immune evolutionary algorithm for locating tropical cyclones. *Atmos. Res.*, 97(1-2), 266-277.
doi:10.1016/j.atmosres.2010.04.015
- Weir, R. C., 1982. Predicting the acceleration of northward-moving tropical cyclones using upper-tropospheric winds. Tech. Rep. No. ADA127446. Naval oceanography command center/Joint typhoon warning center, San Francisco.
- Wiederanders, C. J., 1961. Typhoon forecasting techniques. Presented at the U.S. Asian Weather Symp., John Hay Air Base, Philippine Is.

- WMO., 2010. Annual Joint WMO Technical Progress Report on the Global Data processing and Forecasting System (GDPFS) including Numerical Weather Prediction (NWP) Research Activities: India (Technical) (p. 29).
- Xiao, Q., Zou, X., Pondeva, M., Shapiro, M. A., Velden, C., 2002. Impact of GMS-5 and GOES-9 satellite-derived winds on the prediction of a NORPEX extratropical cyclone. *Mon. Wea. Rev.*, 130(3), 507-528.
- Xu, J., Gray, W. M., 1982. Environmental circulations associated with tropical cyclones experiencing fast, slow, and looping motion. *Atmos. Sci. paper No. 346*. Colorado State University, Fort Collins, CO, 110pp.
- Xu, Y., Neumann, C. J., 1985. A statistical model for the prediction of western North Pacific tropical cyclone motion. NOAA Technical Memorandum NWS NHC 28, 30pp.
- Yang, Y., Wang, J., 2005. An integrated decision method for prediction of tropical cyclone movement by using genetic algorithm. *Science in China, Series D: Earth Sciences*, 48(3), 429-440.
- Yeh, K. S., Côté, J., Gravel, S., Méthot, A., Patoine, A., Roch, M., Staniforth, A., 2002. The CMC-MRB global environmental multiscale (GEM) model. Part III: Nonhydrostatic formulation. *Mon. Wea. Rev.*, 130(2), 339–356.
- Zehr, R. M., 1992. Tropical Cyclogenesis in the Western North Pacific. (Technical No. NESDIS 61). NOAA Technical Memorandum (p. 181pp). Washington, D. C.: U. S. Department of Commerce.