

Statistical Analysis of Simulated Fluid-Dynamic Relationships in Weather and Climate Systems

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Research Article

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Abstract

Fluid dynamics is the theoretical approach used to understand the flow of air and water and transfers of energy within the Earth system. This study investigated the statistical relationships between the selected fluid-dynamic variables related to atmospheric motion, cyclone rotation, atmospheric instability, and ocean heat redistribution. An analysis of 5,000 simulated observations was conducted using descriptive statistics, normality tests, correlation analysis and regression analysis in IBM SPSS Statistics, a quantitative approach. The results reported showed positive relationships between pressure gradient and wind speed ($r = 0.960$), Coriolis force and rotational intensity (Spearman's $\rho = 0.845$), sea surface temperature and atmospheric instability (Spearman's $\rho = 0.934$), and ocean circulation and heat redistribution (Spearman's $\rho = 0.983$). Each of the four associations reported was statistically significant ($p < 0.001$). These results reflect relationships that are strong in the simulated data set. The strength of these links, however, does not by itself prove actual cause or that the models are superior to actual weather forecasting. The study gives a statistical example of some of the relationships that are present in fluid dynamics and notes that there is a need for clear procedures in data generation, physical validation, and comparison with observed meteorological and oceanographic data. These relationships should be further explored with independently validated simulations and observation to determine their applicability to weather and climate systems.

Introduction

Weather and climate are variable parts of the earth system, which affects the ecological systems, human activities and environmental sustainability (Vallis, 2017). Their behavior is closely connected with the flow of air and water, the transfer of energy, and the interaction of atmosphere and oceans (Holton & Hakim, 2013). A theoretical framework for studying these processes and understanding the physical mechanisms involved in the development of weather systems, ocean currents and atmospheric circulation is provided by fluid dynamics (Batchelor, 2000). There is an ongoing exchange of energy, momentum and mass between the atmosphere and oceans. The temperature and pressure differences due to unequal solar heating drive fluid motion and the resulting circulation patterns are affected by gravity, viscosity, and Earth's rotation (Vallis, 2017). These processes are related to phenomena like winds, cyclones, monsoons, ocean currents and regional climate variations. Knowledge of their physical interactions is crucial for the interpretation of the behavior of the atmosphere and oceans.

The Navier–Stokes equations are a set of equations that describe fluid motion in the presence of forces and viscous stresses. They are used in combination with the continuity equation and a suitable energy equation to provide the mathematical framework for atmospheric and ocean modelling (Batchelor, 2000; Kundu et al., 2016). But the nonlinearity of fluid systems and their initial-condition sensitivity make them difficult to simulate numerically and to predict from a few known initial conditions (Lorenz, 1963). Therefore, care must be taken in interpreting statistical relationships between fluid-dynamic variables and distinguishing them from evidence of physical causation.

Pressure-gradient forces play a role in atmospheric motion, and the Coriolis effect is caused by Earth's rotation and affects the direction of large-scale circulation. Sea surface temperature influences heat and moisture fluxes between the ocean and atmosphere, and ocean circulation transports heat from one region to another of the Earth (Holton & Hakim, 2013; Vallis, 2017). The relationships between these processes are physically linked, but depend on the spatial scale, environmental conditions and other interacting variables.

Recent advances in computational techniques have greatly increased the ability to simulate atmospheric and oceanic processes numerically. The numerical weather prediction (NWP) system is based on mathematical models, observations, and data assimilation to predict future atmospheric conditions (Kalnay, 2003). Long-term climate behavior and potential long-term responses to external forcing are also studied using climate models (IPCC, 2023). However, the model uncertainty, computational needs and physical parameterizations' limitations are still significant factors.

While the physics of atmospheric and oceanic motions is known, statistical analysis can be used to show correlations between certain variables in a given data set. But a strong statistical correlation in simulated data does not necessarily imply the same correlation in real atmosphere or ocean of the same magnitude. Such results therefore must be interpreted with a clear description of the process of data generation, and physical validation.

Aim and contribution

In the present study, statistical relationships are investigated among five sets of variables related to the pressure gradients and wind speed, Coriolis force and rotational intensity, sea surface temperature and atmospheric instability, ocean circulation and heat redistribution, and recorded scores for forecasting accuracy. Analysis is performed on a data set of simulated observations (N = 5,000), descriptive statistics, normality tests, correlation analysis, and regression methods are used. A contribution of the study is a statistical analysis of these relationships in the simulated data set. It is not intended to develop new physical laws or show a significant improvement in the predictive ability of the physical laws in real-world applications until further independent validation is performed.

Research Problem

The interactions between atmospheric motion, the rotation of the Earth, ocean temperature and ocean circulation are complex in weather and climate systems. The physical principles governing these processes are known, but there are statistical relationships observed in a simulated set of data that cannot be extrapolated to real atmospheric and oceanic conditions. It is therefore essential to be able to describe clearly the process of data generation and to interpret the statistical results appropriately. This study reviews some of the relationships between selected fluid-dynamic variables as simulated and the limitations of the fluid-dynamic relationships to draw conclusions about weather and climate systems.

Research Objectives

The objectives of this study are:

1. To investigate the statistical link between pressure gradient and wind speed for the simulated data set.
2. To assess the association between Coriolis force and rotational intensity.
3. To examine the relationship between sea surface temperature and atmospheric instability.
4. To examine the statistical relationship between ocean circulation and heat redistribution.
5. To investigate the reported comparison of the accuracy scores of the traditional and CFD-based forecasting.

Literature Review

Fluid dynamics is always recognized as one of the fundamental science disciplines to understand the atmospheric and oceanic processes in weather and climate system (Vallis, 2017). Physical Principles that govern the motion of air and water in the Earth System are employed to control the motion of these fluids and transfer of energy and forces (Kundu et al., 2016). The study of fluid dynamics has thus become an important part of meteorology, climatology and various environmental sciences (Holton & Hakim, 2013).

A major advancements in fluid dynamics is the formulation of the Navier–Stokes equations, which give the mathematical description of the flow of viscous fluids (Batchelor, 2000). The equations are the basis for the modern science of fluid mechanics and have been used in numerous models of the circulation of the atmosphere, oceans and turbulent flow (Batchelor, 2000). But the Navier–Stokes equations are very nonlinear and sensitive to changes in the environment, making numerical solutions of the equations for large-scale natural systems difficult, especially due to the importance of the solutions. (Kundu et al., 2016).

Holton (2012) found that most of the large-scale circulation of the atmosphere is caused by pressure gradients and the heat from differential heating of the Earth's surface. The variations in solar radiation result in variations in temperature which lead to variations in pressure and thus to the development of air masses and wind systems throughout the world. The study pointed out that the primary causes of atmospheric motion and the maintenance of atmospheric circulation in different regions of the world are the pressure gradient forces.

The effects of Earth's rotation on dynamics of the atmosphere have also been much discussed in the literature (Holton, 2012). The Coriolis force is an important force in determining the direction and rotation of large-scale weather systems (Holton & Hakim, 2013). Holton (2012) states that cyclones, anticyclones and storm systems form some sort of rotational pattern due to the Coriolis effect. This rotary movement is crucial for the organization and stabilization of atmospheric circulation and is

important for understanding the behavior of hurricanes, typhoons and storms in mid-latitudes (Holton, 2012).

Another important aspect of the global climate system is ocean circulation. Vallis (2017) noted that oceans and atmosphere interact to help control the distribution of heat and moisture throughout the world. Ocean currents transport heat from the equator to the higher latitudes, which helps to reduce the temperature differences between the poles and the equator and influence regional climates. The study also showed that the disruption of ocean circulation could significantly affect the climate system on a longer time scale and could be a climate variability source (Vallis, 2017).

It has long been recognized that temperature changes, particularly sea surface temperatures, are important factors in determining atmospheric instability and storm development (Trenberth, 2011). This warming of the oceans leads to an increased amount of water being evaporated and moisture being available in the atmosphere to be convected and to increase severe weather events (IPCC, 2023). Increased cyclone intensity, heavy rainfall events and strengthening of the energy transfer in the atmosphere have been demonstrated to occur with increased sea surface temperatures in previous studies (IPCC, 2023).

Over the last few decades, Computational Fluid Dynamics (CFD) has matured to become a very useful tool to analyze complex processes in the atmosphere and ocean (Kalnay, 2003). CFD methods are used in numerical weather prediction (NWP) to model the fluid motion and predict weather conditions (Kalnay, 2003). Improvements in computational power, numerical methods and data assimilation techniques have been noted in the literature as sources of great improvements in forecasting accuracy (Kalnay, 2003). Nevertheless, turbulence modelling, Computational cost, and uncertainty in long term climate projections are still challenges for researchers (IPCC, 2023).

An additional crucial field of study is the turbulent character of systems of weather and climate (Lorenz, 1963). Lorenz's chaos theory showed that making small changes at the start of the atmosphere could make a big change in the outcome (Lorenz, 1963). This sensitivity makes it difficult to predict the behavior of atmospheric systems, and is the reason why there is only limited predictability of the atmosphere in the long-term, despite the development of computational models (Lorenz, 1963). This has contributed to the uncertainty being one of the major concerns in meteorological prediction and climate prediction (IPCC, 2023). Many studies have focused on individual components of the atmosphere, ocean, temperature change and computer modelling, but no one has studied them together and try to understand how these fluid dynamic processes all work together in the formation of weather and regulating the climate (Vallis, 2017; Holton & Hakim, 2013). Given this, the present study aims to fill this gap by studying the interaction of pressure gradients with the Coriolis force, sea surface temperature, ocean circulation and CFD-based modeling in a common framework of fluid dynamics.

Research Hypotheses

H₁: Pressure gradient is positively and significantly associated with wind speed in the simulated dataset.

H₂: Coriolis force is positively and significantly associated with rotational intensity in the simulated dataset.

H₃: Sea surface temperature is positively and significantly associated with atmospheric instability in the simulated dataset.

H₄: Ocean circulation is positively and significantly associated with heat redistribution in the simulated dataset.

H₅: CFD-based forecasting demonstrates significantly higher accuracy than traditional forecasting when evaluated using an appropriate, reproducible, and independently validated comparison procedure.

Methodology

Research Design

The research design used in this study was quantitative hypothesis testing analysis which aimed to analyze the statistical relationship between the variables studied in the fluid dynamics of weather and climate systems. Pressure gradient, Coriolis force, sea surface temperature, ocean circulation, and the corresponding outcome variables were used for the analysis. Data were summarized using descriptive and inferential statistical methods and the reported associations were evaluated.

Data Source and Availability

A data set of 5000 observations of fluid dynamics in weather and climate systems was analyzed. The data was processed in Python (Google Colab) and is publicly available on Kaggle:

<https://www.kaggle.com/datasets/nadianaqvi/fluid-dynamics-in-weather-and-climate-systems>. These variables include pressure gradients, wind speed, Coriolis force, rotational intensity, sea surface temperature, atmospheric instability, ocean circulation and heat redistribution.

Study Variables

The analysis examined the following variable pairs:

- Pressure gradient and wind speed.
- Coriolis force and rotational intensity.
- Sea surface temperature and atmospheric instability.
- Ocean circulation and heat redistribution.

An additional analysis was performed, comparing the accuracy scores reported by the traditional method with the accuracy scores obtained from the CFD model. These variables should be defined, their units should be established, and how they are constructed should be documented prior to the evaluation of the physical meaning or the predictive importance of these variables.

Statistical Analysis

IBM SPSS Statistics was used for the reported statistical analyses. The variables were summarized using descriptive statistics such as means, standard deviations and range. The Kolmogorov–Smirnov and Shapiro–Wilk tests were reported for assessing distributional characteristics. The pressure-gradient relationship was computed using Pearson correlation and the other three using Spearman rank correlation. The direction and strength of association between each variable pair were assessed in these analyses. Regression analyses also were reported to explore the statistical association of each predictor variable and each outcome variable. The regression results need to be compared with the original SPSS output (model specification, coefficient type, standard error, confidence interval, and assumptions). Care needs to be taken in interpreting regression models after Spearman correlation, since they measure different statistical properties. A P value of < 0.05 was considered statistically significant. Reported significance values of 0.000 should be reported as $p < 0.001$, as statistical software rounding does not mean that a probability is exactly zero.

Comparison of Forecasting-Accuracy Scores

A paired-samples t-test was conducted to compare the accuracy scores of traditional methods and CFD-based models for 5,000 paired observations. The results of the test were used to evaluate whether the mean difference between the two methods was statistically significant. However, higher accuracy scores do not necessarily indicate that the CFD- based models perform better in terms of generating more accurate weather or climate forecasts. This would require further validation of the results using a consistent set of criteria for developing the models, measuring accuracy, and comparing the accuracy of the forecasts with the actual weather or climate observations.

Results and findings H1: Pressure Gradient and Atmospheric Motion

Descriptive Statistics

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Pressure Gradient	5000	15.03	4.97	1.00	34.63
Wind Speed	5000	35.58	11.46	-0.74	77.64

Normality Test

Variable	Kolmogorov-Smirnov Sig.	Shapiro-Wilk Sig.	Result
Pressure Gradient	0.593	0.070	Normal
Wind Speed	0.999	0.696	Normal

Correlation Analysis

Regression Analysis

Variables	Pearson Correlation (r)	Sig. (2-tailed)
Pressure Gradient and Wind Speed	0.960	0.000

R	R Square	Adjusted R Square
0.960	0.922	0.922

Coefficients

Predictor	Beta	Sig.
Pressure Gradient	2.211	0.000

Interpretation

The descriptive statistics of the 5,000 observations revealed that the mean value of the pressure gradient was 15.03 (SD = 4.97), with 1.00 to 34.63 distribution, while the mean wind speed was 35.58 (SD = 11.46), ranging from - 0.74 to 77.64. The results of the Kolmogorov–Smirnov and Shapiro–Wilk tests for both considered variables demonstrated significance values higher than .05, which indicated the absence of significant deviations from normality for the given sample. According to the analysis of Pearson’s correlations, there is a very strong positive and statistically significant relationship between the two variables ($r = .960$, $p < .001$). In other words, the increase in the values of the pressure gradient leads to a significant increase in the wind speed values in the sample. Hence, the results of the regression analysis are expected to reveal a strong positive connection between the predictor and the outcome variable. Indeed, the regression model appeared to fit the data very well ($R = .960$), with R^2 equal to .922, which means that 92.2% of variance in the wind speed can be predicted by the pressure gradient. Thus, the regression coefficient (2.211, $p < .001$) demonstrates a statistically significant positive link between the predictor and the outcome. Overall, the results of the statistical analysis demonstrated strong evidence for a significant association between the pressure gradient and wind speed; however, the results should be considered within the context of the dataset, and further

verification should be done to check whether the regression coefficient (2.211) represents an unstandardized coefficient (β) or standardized (Beta).

Result:

Hypothesis Accepted

H₂: Coriolis Force and Cyclone Rotational Behavior

Descriptive Statistics

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Coriolis Force	5000	1.031	0.473	-0.031	1.960
Rotational Intensity	5000	60.647	11.207	27.600	92.812

Normality Test

Variable	Kolmogorov-Smirnov Sig.	Shapiro-Wilk Sig.	Result
Coriolis Force	0.000	0.000	Non-Normal
Rotational Intensity	0.000	0.004	Non-Normal

Correlation Analysis

Spearman Correlation

Variables	Correlation Coefficient (r)	Sig. (2-tailed)
Coriolis Force and Rotational Intensity	0.845	0.000

Regression Analysis

R	R Square	Adjusted R Square
0.845	0.714	0.714

Coefficients

Predictor	Beta	Sig.
Coriolis Force	20.018	0.000

Interpretation

Descriptive statistics for the 5,000 simulated observations showed that the mean Coriolis force was 1.031 (SD = 0.473), with values ranging from - 0.031 to 1.960. The mean rotational intensity was 60.647 (SD = 11.207), with values ranging from 27.600 to 92.812. The Kolmogorov–Smirnov and Shapiro–Wilk tests were statistically significant for both variables ($p < 0.001$ for Coriolis force and $p < 0.05$ for rotational intensity), indicating departures from normality according to these tests. Therefore, Spearman’s rank correlation was used to examine the relationship between the variables. The analysis showed a strong positive association between Coriolis force and rotational intensity (Spearman’s $\rho = 0.845$, $p < 0.001$). The reported regression model had an R^2 of 0.714 and an adjusted R^2 of 0.714, indicating that the model accounted for 71.4% of the variation in rotational intensity within the simulated dataset. These findings support a strong statistical association between the two variables in the simulated observations. However, they do not establish that Coriolis force alone determines rotational intensity or prove that the same relationship applies quantitatively to real atmospheric systems. The physical interpretation depends on the definitions, units, and data-generation procedures used for both variables. The reported regression coefficient of 20.018 was statistically significant ($p < 0.001$). However, its interpretation as a change in rotational intensity per unit increase in Coriolis force should be made only after confirming that 20.018 is the unstandardized regression coefficient (β), rather than the standardized Beta coefficient, in the original SPSS output.

Result

The hypothesis is accepted/supported by the simulated data.

H: Sea Surface Temperature and Atmospheric Instability

Descriptive Statistics

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Sea Surface Temperature	5000	23.457	4.936	15.001	31.998
Atmospheric Instability	5000	23.788	4.229	13.172	34.052

Normality Test

Variable	Kolmogorov-Smirnov Sig.	Shapiro-Wilk Sig.	Result
Sea Surface Temperature	0.000	0.000	Non-Normal
Atmospheric Instability	0.000	0.000	Non-Normal

Correlation Analysis

Spearman Correlation

Variables	Correlation Coefficient (r)	Sig. (2-tailed)
Sea Surface Temperature and Atmospheric Instability	0.934	0.000

Regression Analysis

R	R Square	Adjusted R Square
0.934	0.872	0.872

Coefficients

Predictor	Beta	Sig.
Sea Surface Temperature	0.800	0.000

Interpretation

Descriptive statistics for the 5,000 simulated observations showed that the mean sea surface temperature was 23.457 (SD = 4.936), with values ranging from 15.001 to 31.998. The mean atmospheric instability was 23.788 (SD = 4.229), with values ranging from 13.172 to 34.052.

The Kolmogorov–Smirnov and Shapiro–Wilk tests were statistically significant for both variables ($p < 0.001$), indicating that the tests detected departures from normality. Therefore, Spearman’s rank correlation was used to examine the relationship between sea surface temperature and atmospheric instability.

The results showed a strong positive association between sea surface temperature and atmospheric instability (Spearman’s $\rho = 0.934$, $p < 0.001$). The reported regression model had an R^2 of 0.872 and an

adjusted R² of 0.872, indicating that the model accounted for 87.2% of the variation in atmospheric instability within the simulated dataset.

These findings indicate a strong positive statistical association between the two variables in the simulated observations. However, the results do not establish that higher sea surface temperatures directly cause greater atmospheric instability. The interpretation of this relationship depends on how both variables were defined and generated. Since the dataset consists of simulated observations, further validation using documented physical equations and independent observational data would be required before extending these findings to real weather and climate systems.

The reported regression coefficient for sea surface temperature was 0.800 ($p < 0.001$). Its interpretation as the expected change in atmospheric instability for a one-unit increase in sea surface temperature should be confirmed from the original SPSS output by checking whether 0.800 represents the unstandardized coefficient (β) or standardized coefficient (Beta).

Normality Test (Shapiro-Wilk)

Variable	Statistic	Sig.
Traditional Method Accuracy	0.996	0.326
CFD Model Accuracy	0.997	0.594

Since $p > 0.05$ for both variables, the data are approximately normally distributed.

Correlation Analysis

Variables	Correlation (r)	Sig.
Traditional Method Accuracy & CFD Model Accuracy	0.854	< 0.001

Paired Samples Statistics

Variable	Mean	Std. Deviation	N
Traditional Method Accuracy	72.028	4.982	5000
CFD Model Accuracy	83.994	5.815	5000

Paired Samples t-Test

Comparison	Mean Difference	t-value	Sig.(2-tailed)
CFD Model Accuracy – Traditional Method Accuracy	11.966	279.446	< 0.001

Interpretation

Descriptive statistics were calculated for 5,000 simulated observations. The mean accuracy score for the traditional method was 72.028 (SD = 4.982), whereas the mean accuracy score for the CFD model was 83.994 (SD = 5.815). The Shapiro–Wilk tests were non-significant for both traditional-method accuracy ($p = 0.326$) and CFD-model accuracy ($p = 0.594$), indicating that these tests did not detect significant departures from normality.

The correlation analysis showed a strong positive association between traditional-method accuracy and CFD-model accuracy ($r = 0.854$, $p < 0.001$). This indicates that higher scores for one method tended to be associated with higher scores for the other across the paired observations. However, this correlation does not establish that either method is more accurate.

A paired-samples t-test was reported to compare the two methods. The CFD-model accuracy score had a higher mean than the traditional-method score, with a mean difference of 11.966 points. The reported test was statistically significant, $t(4999) = 279.446$, $p < 0.001$. Thus, the reported scores showed a statistically significant difference between the two methods, with higher average scores for the CFD model.

However, statistical significance alone does not establish that CFD-based models provide more accurate real-world weather and climate predictions. Such a conclusion requires a clear definition of the accuracy metric, documentation of both forecasting methods, comparison against observed weather or climate outcomes, and independent validation using an appropriate test dataset. Because the observations and accuracy scores are simulated, the findings should be treated as a preliminary comparison within the constructed dataset rather than evidence of verified forecasting superiority.

Result

The hypothesis was accepted, as the CFD model showed significantly higher accuracy scores than the traditional method ($p < 0.001$).

Discussion

The results indicated high statistical correlations between the selected fluid-dynamic variables for the analyzed data. These results should be considered in the context of the data and assumptions behind the data, rather than as direct proof of causal relationships in real atmospheric and oceanic systems.

There was a strong positive correlation between pressure gradient and wind speed ($r = 0.960$, $p < 0.001$) for H1. The regression model gave an R^2 of 0.922, which means that 92.2% of the variation in wind speed in the data set is statistically explained by the pressure gradient. This is a relationship that is consistent with what is known in physics that the pressure-gradient forces are part of the physics of atmospheric motion (Holton & Hakim, 2013). However, the present statistical analysis does not prove or establish the

same relationship in observed atmospheric conditions, nor establish the same relationship independently of the other evidence.

It was found that there was a strong positive correlation between Coriolis force and rotational intensity for H₂ (Spearman's $\rho = 0.845$, $p < 0.001$). The reported regression model had an R² of 0.714. These results show an important statistical dependence between the data. It is important to note that the present analysis does not show that Coriolis force is the only force to determine cyclone rotation and intensity, although it is accepted as another part of large-scale atmospheric motion.

The relationship between SST and AI was strong and positive for H₃ (Spearman's $\rho = 0.934$, $p < 0.001$). The R² value in the regression model was 0.872. The pattern is in line with the well-documented phenomenon of the ocean temperature modulating heat and moisture fluxes to the atmosphere. But the analysis does not imply causal effect and/or real-world storm development due to observed statistical relationship. Such an interpretation would require independent observation and well-defined variables.

There was a very strong positive correlation for ocean circulation and heat redistribution in H₄ (Spearman's $\rho = 0.983$, $p < 0.001$). The regression model that was reported gave an R² of 0.964. This relationship is in line with the known relationship between ocean circulation and heat transport between regions (Vallis, 2017). However, the statistical results do not provide evidence for the influence of ocean circulation on global climate regulation. A physical meaning of the variables, their measurement units and the data-generation procedure must be documented prior to drawing wider conclusions.

The traditional method had a mean accuracy score of 72.028, while the CFD model had a mean accuracy score of 83.994 for H₅. The mean difference for the reported paired-samples t-test was 11.966 points ($t = 279.446$, $p < 0.001$). These results indicate that the reported scores differed significantly with higher scores on the CFD model. The comparison does not, however, imply that the model is superior in forecasting accuracy in the real world unless the accuracy measure, the model specifications, the reference observations and the validation procedures are explicitly defined. The reported scores should thus be viewed with some caution.

The results as a whole show good statistical relationships between the selected variables of the analyzed data set. The physical mechanisms discussed are consistent with the principles of atmospheric and oceanic science, and the present analysis does not necessarily demonstrate scientific novelty, causal effects or superior forecasting performance. Reproducibility, transparency of variable construction and validation with independent observational data are areas that should be explored further.

Conclusion

The results indicated significant statistical relationships between the chosen fluid-dynamic variables of the analyzed data set. These results should be interpreted in the context of the data set and the

underlying assumptions, and should not be taken as evidence of causal relationships in actual atmospheric and oceanic systems.

H1 and pressure gradient were highly correlated with a positive relationship ($r = 0.960$; $p < 0.001$). The regression model gave an R^2 value of 0.922, which means that 92.2% of the variation in wind speed in the data could be explained statistically by pressure gradient. The relationship is in agreement with the known physical understanding that pressure gradient forces play a role in the motion of the atmosphere (Holton & Hakim, 2013). However, the current statistical analysis cannot prove causation nor prove the same relationship in observed conditions.

There was a strong positive correlation between Coriolis force and rotational intensity (Spearman's $\rho = 0.845$, $p < 0.001$) for H₂. The reported regression model had an R^2 of 0.714. These results suggest that there is a positive correlation between the data. The present analysis shows that the Coriolis force is a part of the large-scale motion in the atmosphere, but the result does not show that Coriolis force is the only factor that dictates cyclone rotation and intensity.

There was strong positive correlation between sea surface temperature and atmospheric instability for H3 (Spearman's $\rho = 0.934$ and $p < 0.001$). The R^2 value for the regression model was 0.872. This pattern occurred as per the consensus that the ocean temperature can affect heat and moisture fluxes to the atmosphere. But the analysis does not show a direct cause-and-effect relationship or that the statistical relationship found in data reflects actual storm development in nature. What is being suggested here would need to be independently observed and clearly defined variables in order to support such an interpretation.

The correlation between the variables of ocean circulation and heat redistribution was very strong and positive (Spearman's $\rho = 0.983$, $p < 0.001$) for H4. The reported regression model explained the 96.4% of the variance. This correlation is in line with the general belief that the ocean circulation transports heat from one region to another (Vallis, 2017). However, the statistics alone do not prove the impact of the ocean circulation on the global climate control. The physical meaning of the variables, units of measurement, and the way the data were generated should be recorded prior to making generalizations.

The traditional method achieved an accuracy score of 72.028 for H5, while the CFD-model obtained an accuracy score of 83.994. The mean difference for the reported paired-samples t-test was 11.966 points ($t = 279.446$, $p < 0.001$). The results indicate that there is a significant difference between the reported scores with CFD model showing higher scores. But a comparison is not sufficient to prove better real-world forecasting if there is no clear documentation on the accuracy metric, model specification, reference observations and how the model is being validated. So, the reported scores are to be interpreted with caution.

As a whole, the results show that there are strong statistical connections between the variables that were selected in the analyzed dataset. The physical mechanisms presented herein are consistent with those known in the fields of atmospheric and oceanic science, but are not proven to be novel physically

or causally, or to yield better forecasts in and of themselves. Reproducibility, variable construction transparency and validation against independent observational data should be further studied.

Recommendations

The data should be documented in the future, including its source, data-preparation process, variable definitions, measurement units, equations, and assumptions, so the analysis can be reproduced separately. Where simulated observations are used, the simulation process and its limitations should be clearly described.

More research is needed to investigate the reported relationships using current and reliable meteorological and oceanographic data, such as weather-station and satellite data and ocean-monitoring data. Where scientifically justified, other relevant atmospheric and oceanic parameters such as humidity, precipitation, wind shear etc. can be included as additional variables.

A comparison of the CFD-based forecasting with traditional methods should be repeated with clearly defined accuracy metrics, observed results, similar forecasting conditions and independent validation data. Before making conclusions on forecasting performance, researchers should evaluate model assumptions, uncertainty, sensitivity and the reproducibility of reported results.

Finally, future studies could explore applications to regional weather systems, such as monsoons, tropical cyclones, and coastal weather processes. The atmospheric scientists, oceanographers, statisticians, and computational researchers could all benefit from collaboration, in order to draw more reliable conclusions and make better-informed decisions regarding the utility of fluid-dynamic models.

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