Enhancing Terrain Analysis from Digital Elevation Models Using 2-D Kalman FilteringTechnique

Abstract

Three-dimensional spatial information, particularly elevation, is crucial for understanding terrain characteristics essential for meaningful development, often expressed as a Digital Elevation Model (DEM). To achieve reliable and accurate DEM values for terrain analysis, modeling uncertainties is necessary. The primary objective of this study is to determine improved terrain variables from the Digital Elevation Model of the study area.The recursive 2-D Kalman filtering technique was applied four times at different orientations to 121 elevation values extracted from a 30-meter resolution ALOS DEM of the study area using QGIS Desktop 3.22.7 softwareof an area covering approximately 10.80 Hectaresusing QGIS, the process involved 144 iterations. MATLAB was used for the computations.The terrain variables (elevation, first partial derivatives along the X and Y axes) of the central point of the DEM were obtained as a linear combination of the four filtering results. The final estimated values for the central point were 26.5589m for elevation, 0.0002m and 0.0011m for partial derivatives along the X and Y directions, with standard errors of ±0.0001m, ±0.0005m, and ±0.0007m, respectively.A 3-D plot of the terrain surface of the study area using Surfer10 software showed that the recursive 2-D Kalman filtering significantly improved the quality of the terrain surface when applied over the DEM. Therefore, the adopted recursive 2-D Kalman filter is well-suited for terrain surface modeling using grid DEMs. Its use is encouraged for determining improved values of terrain topographic variables, leading to more accurate terrain interpretation. In addition, when compared with ground survey data confirmed the technique's efficiency in reducing DEM noise. These results are promising as they are necessary information for flood route modelling, land use allocation and enhance functionality of the urban space domain of the study area.

(Keywords: Digital Elevation Model, Kalman Filtering, Topographic, Terrain, Spatial Analysis)

1.0 Introduction

Accurate position fixing and the knowledge of terrain nature is paramount for the successful execution of any physical development on land. One of such tools that can be used to study the nature of any terrain, is the Digital Elevation Model (DEM) (Lakshmi &Yarrakula, 2018). A DEM is a 3-D computer representation of the topographic surface of the earth created from elevation data and serves as a veritable tool in surveying, spatial information systems, natural resource management, engineering infrastructure projects, hazard management and risk analysis, agriculture, to mention but a few (Caliper, 2022). DEM can be generated through conventional survey technique or space-based techniques. The former though accurate can be tedious, time consuming and in most cases restricted to a limited area, this has made the utilization of the latter advantageous in that the area of coverage is large and inaccessible area can be easily identified within a short time (Lakshmi &Yarrakula, 2018). Remotely sensed DEMs – referred to throughout this study as DEMs, are generated from data that are originally distorted through sensor, terrain, and atmospheric conditions, leading to misrepresentations (error) in the final product (Smith and Sandwell, 2003; Fisher and Tate, 2006; Nuth and Kääb, 2011). These datasets are commonly received in gridded format and other recently developed adaptive formats (e.g., Liu et al., 2014) – resulting in a defined measurement interval (grid resolution) that may oversimplify fine landscape variability[20-21].

This notwithstanding, elevation values of a DEM derived from satellite images in most cases, are affected by errors. This in turn, tends to inhibit its applications due to the propagation of these to other spatial product derived from the DEM.In practice, DEM users often neglect this fact and assume the DEM to be the true representation of elevation, since it is easily obtained using satellites mostly for wide coverage, as opposed the conventional technique which is deemed accurate but time consuming. It is quite obvious that in spite of the plethora of the DEM, their values are not optimal and cannot be deemed accurate for precise determination of the required terrain variables for accurate terrain interpretation (Marcus, 2023).Thus, it becomes imperative for the uncertainty in DEM values to be assessed so that the propagation of the errors can be accounted for to generate reliable and accurate terrain variables for better terrain interpretation. The variation of DEM values and control points elevations can be determined in most cases and this in turn ascertain the accuracy of the DEM values based on the discrepancy of the elevation errors, (Mandla and Kamal, 2008). Therefore, this research seeks to implement the recursive 2-D estimator attribute of the Kalman filtering technique in the determination of improved terrain variables of DEM, to serve as a veritable geo-solution tool for environmental modelling and geospatial applications.The primary objective of this study is to determine improved terrain variables from the Digital Elevation Model of the study area.

2.0 Study Area

The study area is an open space along the new Port Harcourt International Airport road, located at Aluu in Ikwerre Local Government Area of Rivers State. It is an upland area with a vast arable land thereby making majority of its inhabitant farmers. Geographically, the study area lies within latitude 04^0 58’ 09’’N and longitude 06^0 56’ 55’’E and latitude 04^0 58’ 19’’N and longitude 06^0 56’ 58’’E (Abdullahi, Afolabi, Bosco-AbiahuEze, Phil-Eze, Wali, and Wizor, 2021; Njoku, 2021) as shown in figure 1.

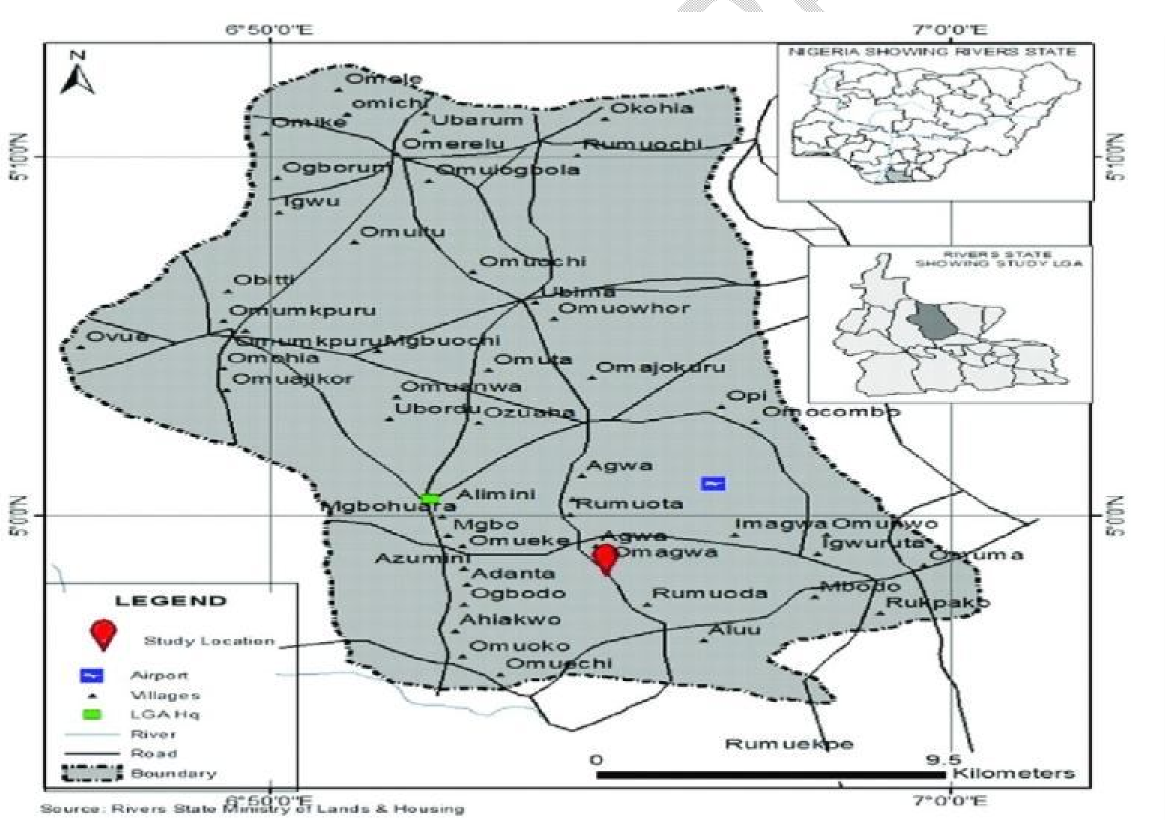


Figure1.: Map of Ikwerre Local Government Area Showing the Study Area (Aluu)
Source: Rivers State Ministry of Lands and Housing Adapted in Abdullahi, Afolabi, Bosco-Abiahu, Eze, Phil-Eze, Wali, &Wizor, (2021).

3.0 Conceptual Review

3.1 Principle of 2-D Kalman Filtering for Digital Elevation Model

The principle of the 2-D Kalman filtering technique is based on the use of relevant observations and, predictions models derived from the orthogonal neighbouring points at positions (i-1, j) and (i,j-1) respectively to improve the value of a DEM point at position (i,j). The essence is to filter the uncertainty in DEM that may occur as a result of process, methods, and procedures of generating the DEM to improve the accuracy of the DEM (Wang, 1998; Marcus, 2023). The output of the process are the estimates of elevations, and their first order partial derivatives, that is, slopes in Eastings and Northings directions, (Cheng, Lu, Trinder, Wang[a]& Wang[b], 2002; Marcus, 2023). One of the key concepts of the Kalman filtering technique is the state of the system to be filtered (Wang 1998). The state of the system, in this case, the DEM, is the minimum amount of information of the past and present estimates needed to determine an optimal casual estimate of the future responses given future noisy observation (Alebooye, Ghannadi., Izadi & Moradi, 2020). The concept of state provides the basis for the formation of a dynamic model to govern the Kalman filtering technique (Wang, 1998, Marcus, 2023). Therefore, to form the state of the system, elevation H(i, j), the first partial derivative of the elevation along the X and Y direction, (slopes along X and Y directions), Hx(i, j) and H y (i, j) respectively were used.

$$S(i,j) = \begin{bmatrix} H(i,j) \\ H_X(i,j) \\ H_Y(i,j) \end{bmatrix} \tag{1}$$

From terrain geometry;

$$\mathrm{H(i,j)} = \mathrm{b(i,j)[H(i-1,j)} + H_X(\mathrm{i}-1,\mathrm{j})d_X] + \mathrm{c(i,j)[H(i,j-1)} + H_Y(\mathrm{i,j}-1)d_Y] + V_H(i,j) \tag{2}$$

$$H_X(i,j) = H_X(\mathrm{i}-1,\mathrm{j})d_X + V_{H_X}(i,j) \tag{3}$$

$$H_Y(i,j) = H_Y(\mathrm{i,j}-1)d_Y + V_{H_Y}(i,j) \tag{4}$$

Where;

$S(i,j)$ = state vector

H (i, j) = elevation of point (i,j),

Hx (i, j), and Hy (i, j) = first partial derivatives of elevation along the X and Y directions of point (i, j) respectively.

H(i -1, j) , Hx (i -1, j) ,and Hy (i, j-1) elevation, and first partial derivatives of elevation along the X and Y direction of point (i -1, j), and (i, j-1) respectively.

dx and d_Y = sampling intervals of the DEM in X and Y direction.

$V_H(i,j), V_{H_X}(i,j), V_{H_Y}(i,j)$ = white noise sequences, which are to be filtered.

Rewriting equations 2, 3 & 4, the dynamic model is formed as (Alebooye, Ghannadi, Izadi, & Moradi, 2020; Marcus,2023):

$$S(i,j) = B(i,j).S(i-1,j) + C(i,j).S(i,j-1) + v_s(i,j) \quad (5)$$

Where:

$$B(i,j) = \begin{bmatrix} b(i,j) & b(i,j)d_x & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$C(i,j) = \begin{bmatrix} c(i,j) & 0 & b(i,j)d_x \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$v_s(i,j) = \begin{bmatrix} v_H(i,j) \\ v_{H_X}(i,j) \\ v_{H_Y}(i,j) \end{bmatrix}$ = white noise with known covariance structure $Q(i,j)$

The functional model is given as (Alebooye, Ghannadi, Izadi, & Moradi, 2020; Marcus,2023):

$$Z(i,j) = D.S(i,j) + v_z(i,j) \quad (6)$$

Where:

$D = [1 \;\; 0 \;\; 0]$,

$v_z(i,j)$ =white sequence with known covariance $R(i,j)$

Equation 6, denotes the linear relationship between observed elevation and state vector at the relevant position.

3.2 Formation of Kalman Filtering Equations

The recursive Kalman filtering equations are given as (Alebooye, Ghannadi, Izadi, & Moradi, 2020; Marcus, 2023):

$$S_x(i,j) = B_x(i,j)S(i-1,j) + V_{S_X}(i,j) \quad (7)$$

$$S_y(i,j) = C_y(i,j)S(i,j-1) + V_{S_y}(i,j) \quad (8)$$

$$S_x^-(i,j) = B_x(i,j)S(i-1,j) \quad (9)$$

$$P_x^-(i,j) = B_x(i,j)P^+(i-1,j)B_x^T(i,j) + Q_x(i,j) \quad (10)$$

$$S_y^-(i,j) = C_y(i,j)S(i,j-1) \quad (11)$$

$$P_y^-(i,j) = C_y(i,j)P^+(i,j-1)C_y^T(i,j) + Q_y(i,j) \quad (12)$$

$$S^{-}(i,j) = P^{-}(i,j)\left[\left(P_x^{-}(i,j)\right)^{-1}S_x^{-}(i,j) + \left(P_y^{-}(i,j)\right)^{-1}S_y^{-}(i,j)\right] \quad (13)$$

$$P^{-}(i,j) = \left[\left(P_x^{-}(i,j)\right)^{-1} + \left(P_y^{-}(i,j)\right)^{-1}\right]^{-1} \quad (14)$$

$$K(i,j) = P^{-}(i,j)D^{T}(DP^{-}(i,j)D^{T} + R(i,j)^{-1} \quad (15)$$

$$S^{+}(i,j) = S^{-}(i,j) + K(i,j)(Z(i,j) - DS^{-}(i,j)) \quad (16)$$

$$P^{+}(i,j) = [I - K(i,j).D].P^{-}(i,j) \quad (17)$$

Where;

$S^{-}(i,j)$= predicted estimate of state vector

$P^{-}(i,j)$= covariance matrix of predicted estimate

$K(i,j)$=kalman gain

$S^{+}(i,j)$=updated estimate of state vector

$P^{+}(i,j)$=covariance matrix of updated estimate

$S_x^{-}(i,j)$, $S_y^{-}(i,j)$, $P_x^{-}(i,j) and P_y^{-}(i,j)$= predicted estimates along orthogonal directions (X and Y) and their associated covariance matrixes.

3.3 Detection and Removal of Outliers

In order to detect outliers from the valid observation of the DEM at an arbitrary point(i,j), an innovation series was formed to depict the difference between predicted estimate and observed elevation. The innovation series is given as (Wang, 1998; Alebooye, Ghannadi, Izadi, & Moradi, 2020; Marcus,2023);

$$L(i,j) = Z(i,j) - H^{-}(i,j) \quad (18)$$

Where:

$L(i,j)$ = innovation series

$H^{-}(i,j)$ = predicted estimate of elevation

$Z(i,j)$ = observed elevation

$L(i,j)$ is a normal distribution statistic variable having a zero mean and a variance $\sigma^2_{L(i,j)}$, given as;

$$\sigma^2_{L(i,j)} = \sqrt{\sigma^2_{H^{-}(i,j)} + R(i,j)} \quad (19)$$

Where:

$\sigma^2_{H^{-}(i,j)}$ = variance associated with predicted estimate of elevation, $H^{-}(i,j)$ and can be obtained through equation 8.

$R(i,j)$ = observation variance known in equation 6

From relevant probability theory, if an observation is quantitatively close to the mean value of zero, (0) then, there is a high probability for it to happen however, if it is far from the mean value of zero then, it will be quite sensible to doubt its validity and reject it. Thus, $L(i,j)$ can be used as a test statistic to detect outliers in elevation measurement based on the following criterion;

$$|R(i,j)| > \xi_{\alpha}.\sigma_{L(i,j)} \quad (20)$$

Where:

ξ_{α} = critical value with a risk level α

The critical value can be calculated mathematically using the risk level. Typically, the risk level is selected as α = 0.1%, 1%, & 5% and their subsequent critical values are given as $\xi_{0.001}$ = 3.89, $\xi_{0.01}$ = 2.58, $\xi_{0.05}$ = 1.96, respectively. For this work, the critical value used is 1.96 which is equivalent to a level of approximation by 95% confidence.

In a case where equation 20 is true then, the measurement $Z(i,j)$ is considered to contain an outlier. Otherwise, the elevation measurement is valid.

Any detected outlier will be removed through the derivation of the Kalman gain in equation (15) by amplifying the measurement error $R(i,j)$ into a large value. By so doing, the effect of the outlier on the current updated estimate of elevation $H^{+}(i,j)$ will be effectively eliminated. The updated estimate of the state vector and its covariance given in equations (16) and (17), will remain stable following their predictions given in equations 13 and 14, respectively

4.0 Materials and Methods

4.1 Data and Software Used

The research materials include:

Data sets: the data sets acquired were from Greater Port Harcourt City Development and ALOS World 3D, AW3D30) DEM of Part of Aluu in Ikwerre Local Government Area for 2022 with a spatial resolution of 30m x 30m. (Source: http://www.eorc.jaxa.jp.ALOS/en/ew3d30/, 30m Research Version released in 2016.This was chosen due to its high-resolution content and availability as at the time of this research. The software and hardware used includes, QGIS, Surfer and MatlabR2018a application software.

The method deployed in this work is systematically described in the schematic diagram as shown in Figure 2. The development of the functional and dynamic models underscores the Kalman Filtering techniques after the outliers are identified and eliminated. The prediction and update phases were generated using the MATLAB application. The improved values as adjusted with associated reliability.The ground survey approach of determination of elevation data was obtained through actual measurement of differences in height in the field connected to a benchmark referenced to Mean Sea Level. The digital level equipment was used to obtain field values from sample points that is deemed to capture the representation of theterrain, (Oba, et al, 2020).Table 1, shows us specimen of ground elevation of selected points in the study area.

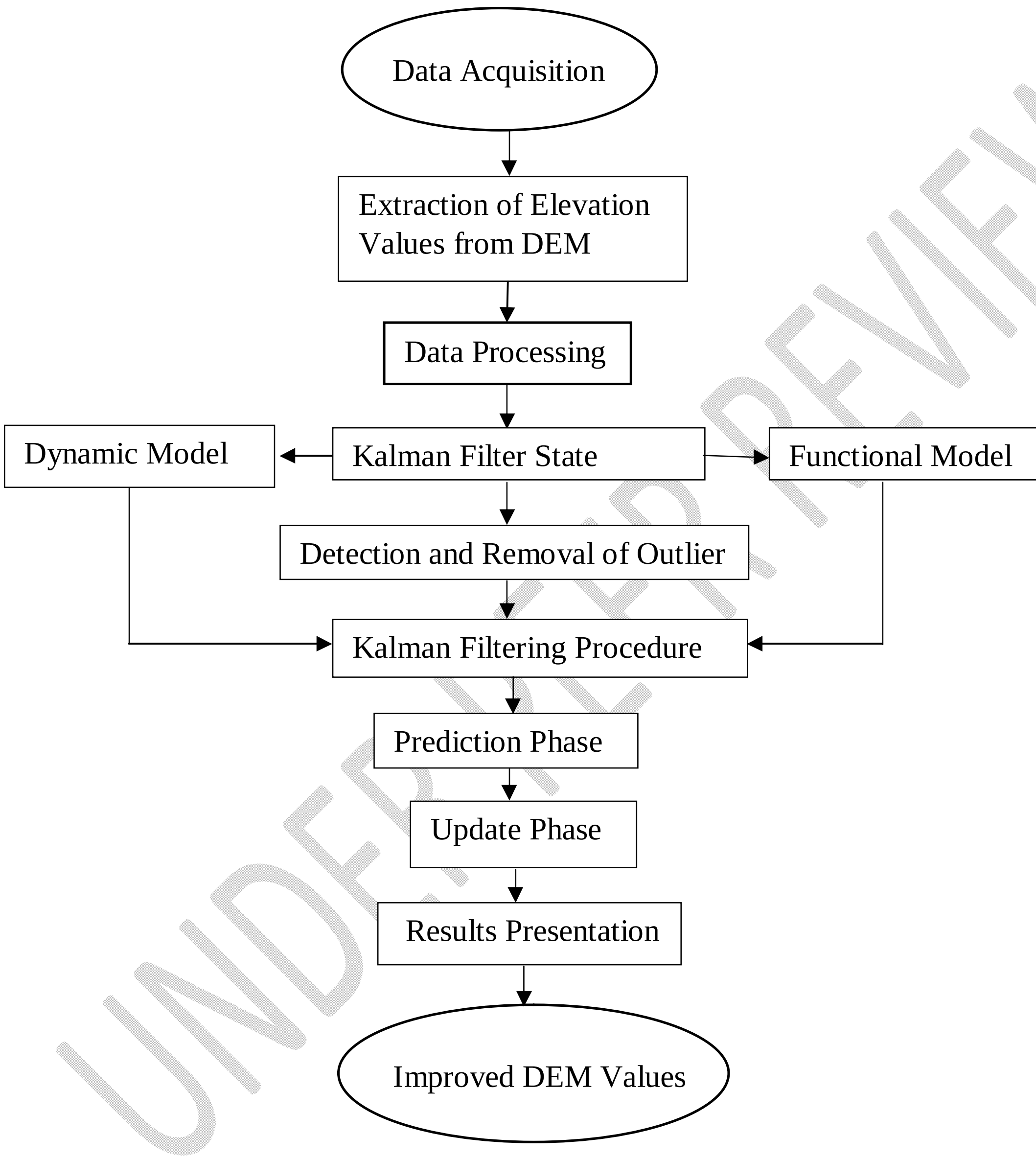


Figure 2.: The Schematic Diagram of the Methodology

4.2 Application of 2-D Kalman Filter

For this work, the recursive 2-D Kalman filter will be deployed in the determination of terrain variables of a digital elevation model. The Kalman filter demonstrates the dynamical time series system for each spatial domain in a spatiotemporal array by a state vector for the single points in time. The state vector contains the change value, the change rate, and the acceleration of change. From this state, a future state can be predicted, and updated and corrected as new observations, (Winiwarter, et al, 2022).

The data used in this work are elevation values extracted froma 30m x 30m spatial resolution ALOS DTM of Part of Aluu in Ikwerre local government area of Rivers State for 2022 as shown in figure 3. and ground elevation values obtained from Greater Port Harcourt City Development as shown in table 1. The ground elevation values were used as validation data to validate the results obtained from the recursive 2-D Kalman filtering technique.

Block Block

28	28	28	27	27	27	27	28	29	30	30
28	28	28	27	27	26	26	26	28	30	30
29	28	28	26	25	25	26	26	27	30	30
30	29	29	27	27	27	27	28	29	29	29
30	29	29	29	29	28	29	30	30	29	28
29	29	30	30	30	29	28	29	30	29	27
28	28	29	29	30	29	28	27	27	27	26
27	25	27	27	29	28	28	27	26	25	26
25	24	25	25	26	25	26	27	27	26	27
26	25	24	24	24	24	26	26	26	26	26

Blo ck

B lo c

Figure 3.: Elevation Values Extracted from the DEM of the Study Area

Table 1.: Specimen of Elevation Values of Selected Points Obtained from Ground Survey of the Study Area

S/N	Elevations from ground survey (meters)	Remark
1	27.9897	Boundary (1)
2	28.0442	Point 29
3	28.0363	Point 38
4	28.9475	Point 51
5	26.5631	Point 61(ij)
6	24.9770	Point 71
7	24.9649	Point 82
8	25.0624	Point 94
9	25.0505	Point 105
10	29.0201	Boundary (111)

Source: Greater Port Harcourt City Development, 2022.

The recursive 2-D Kalman Filtering processor was applied over an 11 by 11 grid DEM of part of Aluu, sampled at 30m intervals along the X and Y axes. A total number of one hundred and twenty-one (121) elevation values where processed. The area of coverage is approximately 10.8 hectares and was divided into four blocks with each block having a total number of thirty-six (36) points as shown in figure 3. The point of interest (ij), which is the midpoint of the DEM, has an elevation value of twenty-nine (29.00m) meters and is common to all the four blocks. In order to determine the estimate of elevation and the first partial derivatives of the midpoint, thirty-six iterations were carried out in each of the blocks, summing up to a total of one hundred and forty-four (144) iterations. The linear combination of the results from the four blocks gave the final state vector ($S_{final}^{+}(i,j)$) and its associated covariance matrix ($P_{final}^{+}(i,j)$), (usually known as the adjusted values) of the central point of the DEM as;

$$S_{final}^{+}(i,j) = P^{++}(i,j)\left[\left(P_1^{+}(i,j)\right)^{-1}S_1^{+}(i,j) + \left(P_2^{-}(i,j)\right)^{-1}S_2^{-}(i,j) + \left(P_3^{+}(i,j)\right)^{-1}S_3^{+}(i,j) + \left(P_4^{-}(i,j)\right)^{-1}S_4^{-}(i,j)\right] \quad (21)$$

$$P^{++}(i,j) = \left[\left(P_1^{+}(i,j)\right)^{-1} + \left(P_2^{-}(i,j)\right)^{-1} + \left(P_3^{+}(i,j)\right)^{-1} + \left(P_2^{-}(i,j)\right)^{-1}\right]^{-1} \quad (22)$$

$$P_{final}^{+}(i,j) = P^{++}(i,j) \quad (23)$$

This was achieved by moving along the strip of each of the blocks at different orientations, by implementing equations 7 through 23 in Matlab R2018a application software and the results has proven the justification and necessity of this research.

5.0 Results and Discussion

Figure 4. and 5. shows the 3D elevation surfaces of the study area obtained from the DEM elevation values and the result of the recursive 2D Kalman filtering technique respectively. Filtering is a common step to smooth DEM noise before deriving geomorphic metrics and improved values of DEM, (Tarolli, P., & Sofia, G., 2016).

The values of Sf in figure 6. are the estimated terrain variables (Elevation (26.5587m), first partial derivatives along X and Y axes (0.0002m, 0.0011m)) of the central point (ij).10.74% of the entire DEM data were used to validate the result of the 2-D Kalman Filtering Technique. Figure 7. shows the difference between elevation values obtained from the 2-D Kalman filtering result and elevation values extracted from ground survey while figure 8. shows the difference between elevation values extracted from the DEM and elevation values extracted from ground survey.

Results from figures 4, 8. are a clear indication that the recursive 2-D Kalman Filtering technique has successfully filtered and smoothened out the noise associated with the DEM of the study area by incorporating all DEM points in deriving the estimate of elevation and first partial derivatives along X and Y axes of the central point (that is point 61) of the DEM from which other terrain attributes can be determined by environmentalist, urban planners, geomaticians and allied professionals for better terrain analysis.

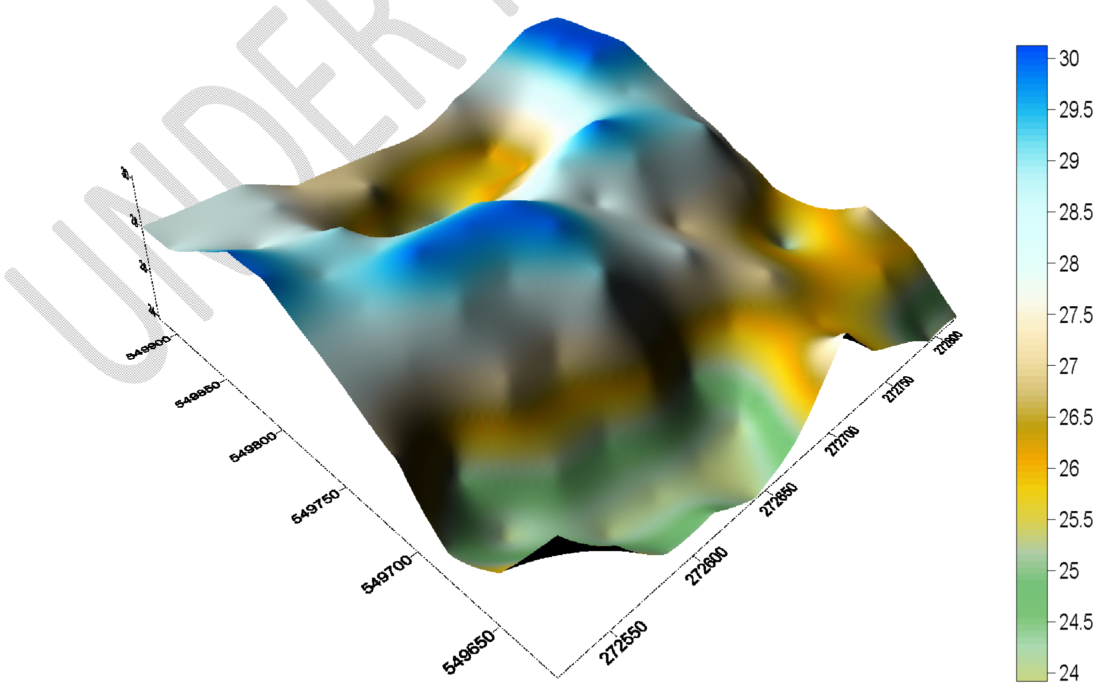


Figure 4.: 3D Elevation Surface of the Study Area Obtained from DEM Elevation Values

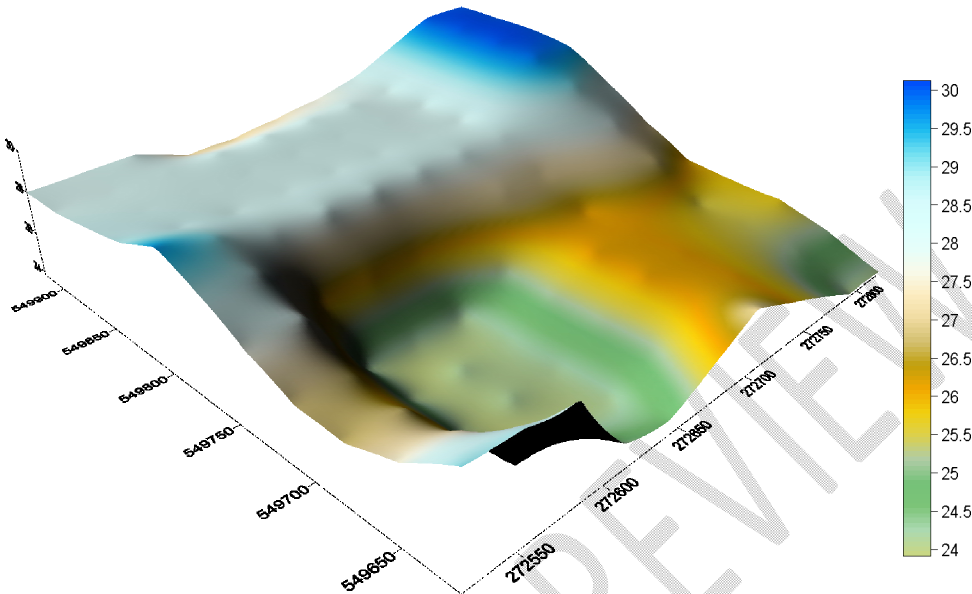


Figure 5.: 3D Elevation Surface of the Study Area Obtained from 2D Kalman Filtering results

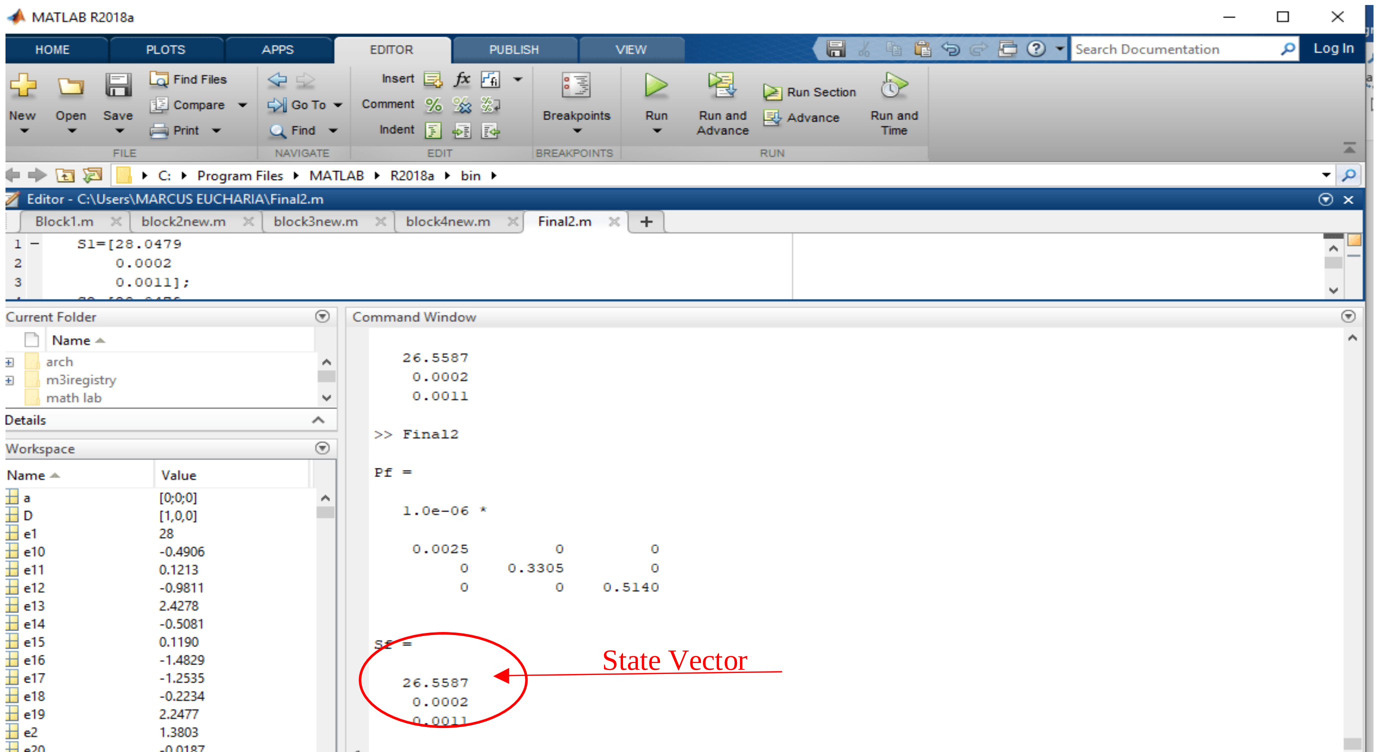
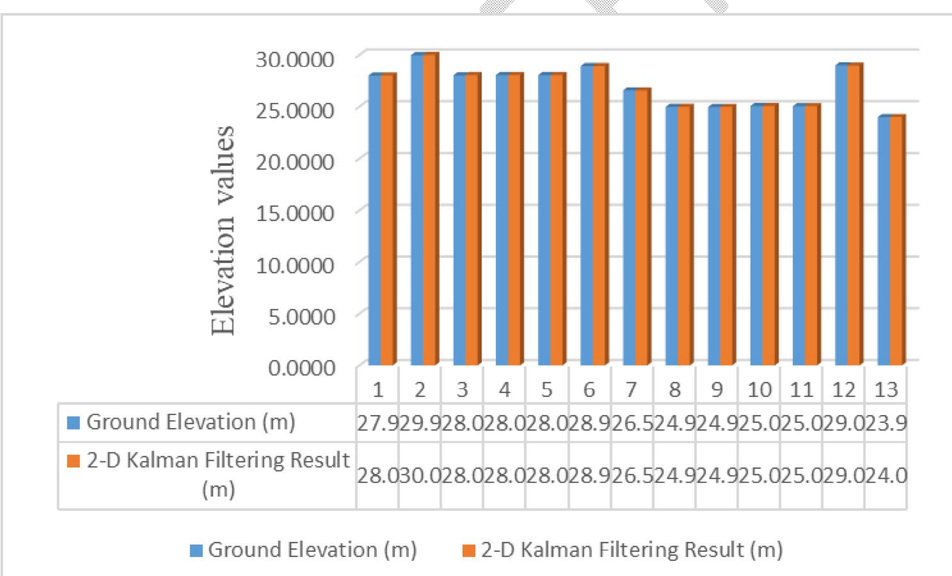


Figure 6.: Estimates of Terrain Variables of Point (ij) Obtained from 2-D Kalman Filtering Results



	1	2	3	4	5	6	7	8	9	10	11	12	13
Ground Elevation (m)	27.9	29.9	28.0	28.0	28.0	28.9	26.5	24.9	24.9	25.0	25.0	29.0	23.9
2-D Kalman Filtering Result (m)	28.0	30.0	28.0	28.0	28.0	28.9	26.5	24.9	24.9	25.0	25.0	29.0	24.0

Figure 7.: Difference between 2-D Kalman Filtering Result and Elevation Values Extracted from Ground Survey Values

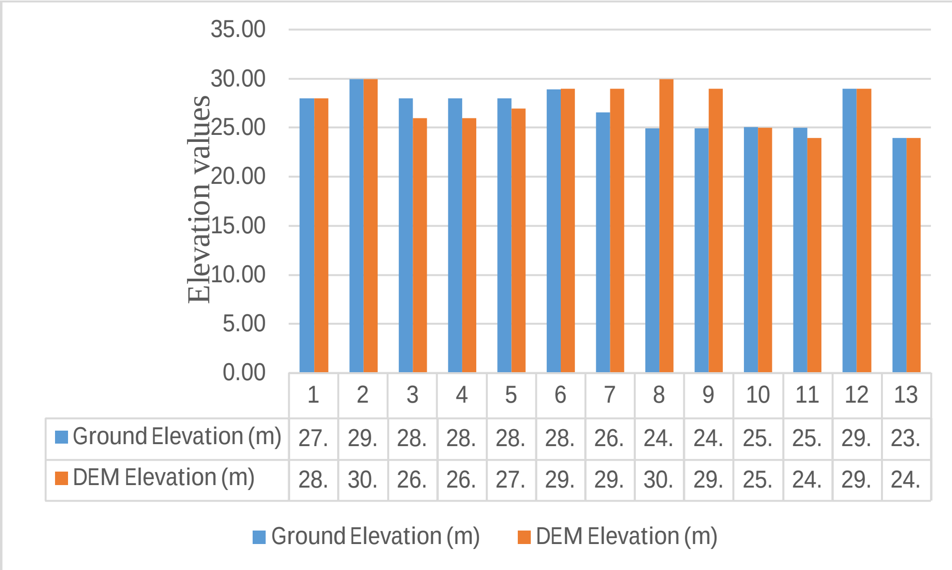


Figure 8.: Difference between Elevation Values Extracted from DEM and Ground Survey Values

6.0 Conclusion

The adopted 2-D Kalman filter was applied over a 30-meter resolution ALOS DEM of the study area, and the results were compared with those from a ground survey. The findings indicated that the 2-D Kalman filter efficiently reduces the effect of DEM noise when deriving terrain topographic variables. The significant improvement in the quality of the terrain surface model, as shown in Figure 5, validates the effectiveness of the recursive 2-D Kalman filter. Therefore, the 2-D Kalman filter is recommended for terrain surface modeling using grid DEMs, as it provides improved values of terrain topographic variables for accurate terrain interpretation. The significance of this work guarantees optimal flood routing model necessary for storm water canal design, land use allocation in relation to urban space of the study area.They are also important for watershed management and erosion control. The government agencies and environmentalist will find the information veritable for sustained environmental management. Future research could explore the application of this technique in different terrains and with higher resolution DEM data.

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Details of the AI usage are given below:

1.

2.

3.

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