**" Comparison of Aqua MODIS Sea Surface Temperature DN values Extracted from SeaDAS and ArcGIS at Bay of Bengal”**

**ABSTARCT**

This study compares Sea Surface Temperature (SST) DN values extracted from Aqua MODIS data using SeaDAS and ArcGIS of Visakhapatnam coastal waters, Bay of Bengal (BOB), India. SST data from January to December 2024 were analyzed across buffer zones of 50km ,75km,100km,125km,150km,200 km to assess their performance in zonal statistics. Both tools showed high consistency, with absolute errors ranging from 0.000007°C to 0.000163°C and APE from 0.000023 to 0.000563. Errors were negligible up to 150 km, but a one-pixel discrepancy observed at 200 km buffer, which slightly increase the error percentage. Seasonal pixel fluctuations, notably a 15-20% drop in July due to monsoon cloud cover, were observed. Both tools proved reliable for zone delineation, with negligible errors well below the ecological thresholds. SeaDAS excelled in precise SST processing, while ArcGIS offered superior geospatial visualization.

**Key Words-***Sea Surface Temperature, Buffer zone****,*** *Zonal Statistics, Aqua MODIS*

1. **INTRODUCTION**

Remote sensing plays a crucial role in monitoring and analysing Sea Surface Temperature (SST), as in-situ observations are often limited in frequency and spatial coverage. SST serves as a key indicator of climate system dynamics. Analysing SST distributions through remote sensing offers insights into ocean-atmosphere interactions and global climate patterns (Das, 2024). Remote sensing data facilitate the continuous monitoring of climate variables on regional and global scales, supporting assessments of climate change impacts and adaptation strategies (Gabriele et al., 2023). Remote sensing technologies, integrating both active and passive sensors across the electromagnetic spectrum, are pivotal in the comprehensive observation of oceanic parameters, with particular emphasis on SST dynamics (Devi et al., 2015). Various satellite sensors are employed to measure SST, including the Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High-Resolution Radiometer (AVHRR), and Sea-viewing Wide Field-of-view Sensor (SeaWiFS). Such data are essential for detecting temperature fluctuations, assessing climate change, and informing marine resource management strategies (Dunstan et al., 2018). Among the various methodologies for spatial SST analysis, Region of Interest (ROI) extraction plays a pivotal role in delineating specific zones, analysing coastal influences, and evaluating the impact of spatio-temporal variations on marine biodiversity. Multiple approaches exist for retrieving remote sensing data from satellite imagery. Scholars or Researchers who has no knowledge of coding on extraction of SST value, the tools SeaDAS and ArcGIS will give Zonal Statistics of study area. SeaDAS is a free, open-source software designed for data processing, visualization, and geospatial analysis, particularly for oceanographic applications. In contrast, ArcGIS is a licensed software renowned for its capabilities in mapping, multilayer analysis, and advanced geospatial analysis. A comparative evaluation of these tools will provide insights into their effectiveness in extracting zonal statistics and analyzing SST variations.

Discuss more about the study of the art with the new articles, as such as some articles in the end of the text.

**2. MATERIALS AND METHODS**

**2.1 Study Area**

The study area includes the coastal waters of Visakhapatnam district in northern Andhra Pradesh, located in the Bay of Bengal at approximately 17.695° N latitude and 83.3025° E longitude. This study established multiple buffer zones extending from the Visakhapatnam fishing harbour with radii of 50 km, 75 km, 100 km, 125 km, 150 km, and 200 km. The Bay of Bengal is the largest bay in the world and is part of the Indian Ocean. It supports a diverse range of marine flora and fauna and is responsible for nearly 7% of the world's total fish catch (Transboundary Diagnostic Analysis, Vol. 2). Therefore, monitoring this region can be an effective strategy for delineating fishing zones and predicting fisheries yields. (Figure :1)

**Figure 1:Study Area**

**2.2 SeaDAS (Sea, Earth and Atmosphere Data Analysis System)**

SeaDAS, which is developed by NASA, is a special tool for the processing of ocean color data and thermal infrared satellite imagery. It offers advanced functions such as atmospheric correction, radiometric calibration, spectral analysis, and time-series studies, making it a preferred choice for researchers dealing with satellite-derived ocean parameters, particularly suitable for marine and coastal studies. SeaDAS ensures high accuracy in SST retrieval through a combination of remote sensing algorithms. Its open-source nature and user-friendly interface help in the exploration of complex datasets, supporting interdisciplinary studies on climate change and marine ecosystems. Read and reference Salah et al. (2025)….

**2.3 ArcGIS (Arc Geographic Information System)**

ArcGIS, developed by Esri, is a software platform that helps users create, manage, analyse, and map data. It is a widely used Geographic Information System (GIS) that provides advanced geospatial analysis tools, including buffer creation, spatial interpolation, data integration,mapping, and statistical modelling. ArcGIS excels in spatial visualization, making it an excellent choice for buffer zones, integrating multiple environmental datasets, and conducting geostatistical and zonal statistical analyses. The advantage of ArcGIS is to overlay different spatial layers and perform spatial queries, which enhances its applicability in marine studies, particularly in analysing SST gradients and their influence on coastal and offshore environments. GIS enables the analysis of long-term climate data, including trends in temperature, sea level rise, and changes in ice cover and vegetation. Read and cite some recent articles as such as listed in the end, as such as Reitberger et al. (2025), Wang et al. (2025a), for example.

**2.4 Satellite-Derived Sea Surface Temperature**

Monitoring SST is essential for understanding various scientific phenomena, including sea level rise, salinity, upwelling, Potential Fishing Zones (PFZ), eddies, and cyclone (Madhavan et al., 2013). One major advantage of using satellite remote sensing for SST is its ability to collect data across vast areas in near real-time (Kohtaro Hosoda et al., 2007). Satellite sensors such as MODIS, AVHRR and SeaWiFS can capture brightness values across different spectral bands. For this study, 12 monthly level 3 Aqua MODIS satellite images, each with a resolution of 4 × 4 km, have been downloaded from the NASA Ocean Color website (<https://oceandata.sci.gsfc.nasa.gov/l3/>) for the period from January to December 2024.The Aqua MODIS SST retrieval algorithm is given below.

SST=aij0+aij1BT11μm+aij2(BT11μm−BT12μm) Tsfc+aij3(sec(θ−1) (BT11μm−BT12μm) +aij4(mirror)+aij5(θ∗) +aij6(θ2)

**2.6 Methodology**

The methodology involves two types of DN value Extraction for summarizing statistics in a specific buffer zone or polygon from the downloaded image using SeaDAS and ArcGIS. Images downloaded from the NASA website are in NetCDF format. Initially a buffer zone was created in ArcGIS in the form of shapefile for the Region of Interest (ROI). In this study, the shapefile is created with six different radii of buffer having a distance of 50km, 75km, 100km, 125km,150km, 200 km from the Visakhapatnam fishing harbor as our ROI.

**2.6.1 Extraction Of DN Value From Image Through SeaDAS**

Put the coordinate system and corner coordinates here in this map.

**Figure 2: SST image of SeaDAS with Vector File**

As an initial step, it is necessary to load the downloaded NetCDF file into SeaDAS. Then, access the file manager and open the file. Within this, there are various folders, and we need to open the "bands" folder and select the "sst" band, which corresponds to the SST satellite image. The SST image will then be displayed. Now we need to add land mask, which is present in the tool bar. Next, add the ROI shapefile by following these steps: Go to the vector menu in the toolbar, click on "Import," then choose "ESRI shapefile," and select the Multi buffer shapefile. This action overlays the vector shapefile on the Net CDF SST image, which can be seen in the following image (Figure2). Now, navigate to the analysis section in the toolbar and click on "Statistics" to obtain the summary statistics. In the dialog box, we can observe various headings, including "bands," "ROImask," and "Flagmask." Click on the "band" option, then select "sst". For the ROI-Mask, click on the Multi buffer shapefile, at the bottom, select "Individual" on “Mask grouping" and finally click on "Run." The statistics will be displayed on the screen. This outlines the methodology for extracting statistics for an ROI in SeaDAS providing a straightforward approach for oceanographic data analysis (Alaudin et al., 2024).The entire process is depicted in flow chart as figure: 3.

**Create Region of Interest shape file using ArcGIS**

**Download L3 Aqua MODIS SST images**

**Load image into SeaDAS**

**Load vector File**

**(Shape File)**

**Open SST Band**

**Statistical Analysis**

**Load image into SeaDAS**

**Open SST Band**

**Export file as Geo Tiff**

**Load Geo Tiff into ArcGIS**

**Geo Processing**

**(Raster Calculator)**

**Zonal Statistics**

**IN SeaDAS**

**IN ArcGIS**

**Figure 3: Flow Chart of Methodology**

**2.6.2 Extraction Of Dn Value From Image Through ArcGIS**

To extract SST data in ArcGIS, it is necessary to convert the image format from Net CDF to Geo TIFF, as Net CDF files are not supported in ArcGIS. For that in SeaDAS, load the SST Net CDF file, open the " sst" band, now apply the land mask present in the tool bar and proceed to the file menu in the toolbar, and export the file as a Geo TIFF file format. Next, open ArcGIS and load the TIFF file of SST into it. We then use various geoprocessing methods to remove negative values present in the data. Then to get the DN value of SST by opening the zonal statistics tool in the geoprocessing menu and select "Zonal Statistics as Table." For the input raster or feature zone data at the top, give input as ROI file. Next for the Zone Field, select the appropriate ID and for the Value Raster and give input as processed raster. It gives various statistical types such as mean, median, and standard deviation. In this study, the saved mean value from the ROI is used for comparison. This outlines the methodology used for extracting summary statistics is available in ArcGIS manual (Esri, n.d. 2025). The entire process is depicted in flow chart as figure: 3.

**2.7 Methods Of Evaluation**

The Absolute Percentage Error (APE) was utilized to quantify the difference between the mean values derived from SeaDAS and ArcGIS, enabling a comparative assessment of the two data extraction approaches.

$$APE= Abs \left( \frac{ArcGIS-SeaDAS}{ArcGIS}\right)×100$$

It could be applied the kappa index for example. The are many material with this theme (see thematic control quality bibliography recommendations). I think you can read some material apointed in the and of the text too.

**RESULTS AND DISCUSSION**

The dataset examines SST in the coastal waters of Visakhapatnam in the Bay of Bengal, comparing ArcGIS and SeaDAS datasets across multiple buffer zones (50 km to 200 km). The analysis provides insights into seasonal variations, spatial patterns, and the accuracy of ArcGIS relative to SeaDAS. Further using metrics such as mean SST, error values, and APE. Below is a detailed discussion of the results.

From Table 1, it is observed that January had a very minor error in the buffers ranging from 50 to 150 km. The number of valid pixels is equal, and the mean values are so similar that the error exists only in the sixth decimal place, which can be considered negligible. However, in the 200 km buffer, there is a discrepancy of 1 pixel: SeaDAS shows 3,426 pixels, while ArcGIS shows 3,427 pixels. This results in a higher error in this buffer compared to the others (50-150 km). In the 200 km buffer, we can see the error value of 0.000118 and the APE as 0.000443.

In February month, a small error in the 50-150 km buffers. The number of valid pixels remains equal, and the mean values are similar enough that the error is negligible to the sixth decimal. In the 200 km buffer, SeaDAS shows 3,375 pixels, while ArcGIS shows 3,376 pixels, resulting in a higher error percentage in this buffer. In the 200 km buffer, we can find the error value of 0.000106 and APE as 0.000383.

In March we again see a very slight margin of error in the 50-150 km buffers, with equal valid pixel counts and similar mean values. However, in the 200 km buffer, SeaDAS lists 3,326 pixels while ArcGIS has 3,327 pixels, resulting in a higher error in this buffer. For the 200 km buffer, the error value is 0.000163, and the APE is 0.000563.

In April, a similar trend appears in checking for errors in the 50-150 km buffers, where valid pixel counts are equal and mean values are very close. In the 200 km buffer, SeaDAS shows 3,339 pixels compared to 3,340 in ArcGIS, leading to a higher error in this buffer. For the 200 km buffer, we can see the error value of 0.000069 and APE as 0.000226.

In May, we again observed minimal error in the 50-150 km buffers, where valid pixel counts are equal, and mean values are very similar. Hence, the error is negligible to the sixth decimal. In the 200 km buffer, SeaDAS shows 3,461 pixels, while ArcGIS shows 3,462 pixels, resulting in a higher error in this buffer. The error value for the 200 km buffer is 0.000094, and the APE is 0.000299.

In June, we see minimal errors in the 50-150 km buffers, with equal valid pixel counts and very similar mean values, leading to negligible errors in the sixth decimal. In the 200 km buffer, SeaDAS has 3,455 pixels, while ArcGIS has 3,456 pixels, resulting in a higher error level in this buffer. The error value for the 200 km buffer is 0.000007 and the APE is 0.000023.

From Table 2, In July, we can observe that there is a very minute error in the pixel counts for buffers ranging from 50 to 150 km. The number of valid pixels is equal, and the mean values are so similar that the error is only in the sixth decimal place, making it negligible. However, in the 200 km buffer, there is a discrepancy of 1 pixel, SeaDAS has 2957 pixels, while ArcGIS has 2958 pixels. This discrepancy results in a higher error in this buffer compared to the remaining buffers (50-150 km). In the 200 km buffer, the error value is 0.000115, and the APE is 0.000403.

In August, we again note the minute errors in buffers ranging from 50 to 150 km, where the number of valid pixels is equal and the mean values are quite similar, making the error negligible. However, in the 200 km buffer, SeaDAS shows 3,345 pixels, while ArcGIS shows 3,346 pixels, resulting in a higher error in this buffer compared to the others (50-150 km). The error value for the 200 km buffer is 0.000137 and the APE is 0.000464.

In September, presents similar findings. There are minute errors in the 50 to 150 km buffers, but in the 200 km buffer, we note a discrepancy of 1 pixel: SeaDAS has 3,607 pixels, while ArcGIS has 3,608 pixels. This leads to a higher error in this buffer compared to the previous ones (50-150). The error value for the 200 km buffer is 0.000087, and the APE is 0.000291.

In October also shows very minute errors in buffers 50 to 150 km, but a discrepancy of 1 pixel occurs in the 200 km buffer: SeaDAS has 3,885 pixels compared to ArcGIS's 3,886 pixels, resulting in a significant error in this buffer. The error value for the 200 km buffer is 0.000070, and the APE is 0.000228.

In November, highlights very minute errors in the 50 to 150 km buffers. However, for the 200 km buffer, there is a discrepancy of 1 pixel: SeaDAS has 3,882 pixels while ArcGIS has 3,883 pixels, resulting in a notable error in this buffer compared to the others (50-150). The error value for the 200 km buffer is 0.000045, and the APE is 0.000157.

In December, we can observe that there is a very minor error in the 50-150 km buffers. The number of valid pixels is equal, and the mean values are so similar that the error is only in the sixth decimal place, making it negligible. However, in the 200 km buffer, there is a discrepancy of one pixel: SeaDAS shows 3,881 pixels while ArcGIS shows 3,882 pixels. This discrepancy results in a higher error in this buffer compared to the 50-150 km buffers. In the 200 km buffer, the error value is 0.000068 and the APE is 0.000249.

It is evident that there is minimal absolute error between the values obtained from the two methods(Table-3). The error values are found within the range 0.000007 to 0.000163. We can see differing of error values across the different months. The minimal error 0.000007 occurs in June and then in November at 0.000045. The highest error is observed in March at 0.000163, followed by August at 0.000137. The lowest APE is found in June at 0.000023, followed by November at 0.000157. The highest APE is recorded in March at 0.000563, followed by August at 0.000464.

The data indicates that the number of valid pixels fluctuates from month to month in SST readings (Figure-4). Notably, highest number of valid pixels is observed in October, November, and December. In contrast, there is a gradual decline in the number of valid pixels during the month of July across all buffers. Similar findings were reported by Redfern et al. (2023) in his study, who also noted missing pixels during July (2020). During the monsoon, there is a data gap of about 15-20%. However, Amzi et al. (2015) found that there is a 50-60% gap in data during the monsoon season at Mumbai coast in Arabian Sea in the year.

**Figure 4: Pixel Number of ArcGIS at different Buffer Zones**

**CONCLUSION**

This study assessed the performance of SeaDAS and ArcGIS in extracting zonal statistics for SST analysis in the coastal waters of Visakhapatnam, Bay of Bengal, using Aqua MODIS satellite imagery from January to December 2024 across buffer zones of 50–200 km. Both tools yielded highly consistent mean SST values, with absolute errors ranging from 0.000007 to 0.000163°C and absolute percentage errors (APE) from 0.000023 to 0.000563. Errors remained negligible up to 150 km, but a consistent one-pixel discrepancy at 200 km slightly elevated errors, peaking in March (0.000163°C) and minimizing in June (0.000007°C). SeaDAS is an open-source free software, offers superior precision for processing satellite-derived Net CDF data, making it ideal for researchers prioritizing SST accuracy in oceanographic studies. ArcGIS, despite requiring format conversion, excels in geospatial visualization and multilayer integration, enhancing its utility for comprehensive marine and climate analyses. For fishery zone delineation in the Bay of Bengal, both tools are reliable, as errors below 0.0002°C fall well below typical SST thresholds (0.5°C) for ecological impacts. The choice depends on user needs: SeaDAS for rapid, precise processing, and ArcGIS for advanced spatial presentation. Future research should address monsoon-related data gaps, which reduce pixel counts by 15-20% in July, to improve SST retrieval accuracy in tropical regions.

It is necessary rewrite the results and discussion and the conclusion after the recommendations (see thematic control quality bibliography recommendations).

**DISCLAIMER (ARTIFICIAL INTELLIGENCE)**

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image

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**APPENDIX**

**Table 1:Monthly analysis From January to June**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **ArcGIS** | **SeaDAS** |  |  |
|  | **Buffer in km** | **Pixel** | **Mean** | **Pixel** | **Mean** | **Error** | **APE** |
| **January** | 50 | 234 | 25.874762 | 234 | 25.874764 | 0.000002 | 0.000009 |
| 75 | 519 | 26.001261 | 519 | 26.001261 | 0.000000 | 0.000001 |
| 100 | 898 | 26.115992 | 898 | 26.115991 | 0.000001 | 0.000002 |
| 125 | 1375 | 26.229845 | 1375 | 26.229847 | 0.000002 | 0.000007 |
| 150 | 1951 | 26.351080 | 1951 | 26.351078 | 0.000002 | 0.000007 |
| **200** | **3427** | **26.546511** | **3426** | **26.546393** | **0.000118** | **0.000443** |
| **Febuaruy** | 50 | 234 | 27.279337 | 234 | 27.279337 | 0.000000 | 0.000000 |
| 75 | 516 | 27.358837 | 516 | 27.358837 | 0.000000 | 0.000000 |
| 100 | 895 | 27.404587 | 895 | 27.404586 | 0.000001 | 0.000003 |
| 125 | 1366 | 27.431904 | 1366 | 27.431903 | 0.000001 | 0.000003 |
| 150 | 1929 | 27.486904 | 1929 | 27.486904 | 0.000000 | 0.000001 |
| **200** | **3376** | **27.627579** | **3375** | **27.627473** | **0.000106** | **0.000383** |
| **March** | 50 | 232 | 28.711809 | 232 | 28.711810 | 0.000001 | 0.000003 |
| 75 | 511 | 28.773289 | 511 | 28.773287 | 0.000002 | 0.000006 |
| 100 | 895 | 28.885658 | 895 | 28.885659 | 0.000001 | 0.000003 |
| 125 | 1364 | 28.938021 | 1364 | 28.938020 | 0.000001 | 0.000002 |
| 150 | 1914 | 28.955896 | 1914 | 28.955895 | 0.000001 | 0.000005 |
| **200** | **3327** | **29.003969** | **3326** | **29.003806** | **0.000163** | **0.000563** |
| **April** | 50 | 235 | 30.102489 | 235 | 30.102489 | 0.000000 | 0.000002 |
| 75 | 514 | 30.138083 | 514 | 30.138083 | 0.000000 | 0.000002 |
| 100 | 893 | 30.159155 | 893 | 30.159154 | 0.000001 | 0.000003 |
| 125 | 1358 | 30.161255 | 1358 | 30.161255 | 0.000000 | 0.000000 |
| 150 | 1916 | 30.203268 | 1916 | 30.203267 | 0.000001 | 0.000003 |
| **200** | **3340** | **30.305183** | **3339** | **30.305252** | **0.000069** | **0.000226** |
| **May** | 50 | 244 | 30.826332 | 244 | 30.826331 | 0.000001 | 0.000004 |
| 75 | 530 | 30.947727 | 530 | 30.947726 | 0.000001 | 0.000004 |
| 100 | 916 | 30.984192 | 916 | 30.984191 | 0.000001 | 0.000003 |
| 125 | 1394 | 31.015451 | 1394 | 31.015451 | 0.000000 | 0.000001 |
| 150 | 1988 | 31.145554 | 1988 | 31.145555 | 0.000001 | 0.000005 |
| **200** | **3462** | **31.343615** | **3461** | **31.343521** | **0.000094** | **0.000299** |
| **June** | 50 | 246 | 30.260061 | 246 | 30.260060 | 0.000001 | 0.000004 |
| 75 | 535 | 30.269785 | 535 | 30.269784 | 0.000001 | 0.000003 |
| 100 | 923 | 30.311268 | 923 | 30.311267 | 0.000001 | 0.000003 |
| 125 | 1411 | 30.381163 | 1411 | 30.381165 | 0.000002 | 0.000008 |
| 150 | 1987 | 30.410921 | 1987 | 30.410920 | 0.000001 | 0.000004 |
| **200** | **3456** | **30.579834** | **3455** | **30.579827** | **0.000007** | **0.000023** |

**Table 2: Monthly Analysis from July to December**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **ArcGIS** | **SeaDAS** |  |  |
|  | **Buffer In Km** | **Pixel** | **Mean** | **Pixel** | **Mean** | **Error** | **APE** |
| **July** | 50 | 111 | 27.963554 | 111 | 27.963558 | 0.000004 | 0.000013 |
| 75 | 340 | 28.130718 | 340 | 28.130720 | 0.000002 | 0.000006 |
| 100 | 694 | 28.189150 | 694 | 28.189149 | 0.000001 | 0.000003 |
| 125 | 1114 | 28.310106 | 1114 | 28.310107 | 0.000001 | 0.000003 |
| 150 | 1596 | 28.364578 | 1596 | 28.364580 | 0.000002 | 0.000006 |
| **200** | **2958** | **28.510481** | **2957** | **28.510366** | **0.000115** | **0.000403** |
| **August** | 50 | 232 | 29.496292 | 232 | 29.496292 | 0.000000 | 0.000000 |
| 75 | 509 | 29.370001 | 509 | 29.369999 | 0.000002 | 0.000006 |
| 100 | 893 | 29.340469 | 893 | 29.340470 | 0.000001 | 0.000002 |
| 125 | 1346 | 29.391842 | 1346 | 29.391842 | 0.000000 | 0.000000 |
| 150 | 1932 | 29.396414 | 1932 | 29.396412 | 0.000002 | 0.000006 |
| **200** | **3346** | **29.423143** | **3345** | **29.423280** | **0.000137** | **0.000464** |
| **September** | 50 | 252 | 29.875872 | 252 | 29.875872 | 0.000000 | 0.000001 |
| 75 | 540 | 29.866222 | 540 | 29.866222 | 0.000000 | 0.000001 |
| 100 | 929 | 29.759581 | 929 | 29.759580 | 0.000001 | 0.000002 |
| 125 | 1415 | 29.709610 | 1415 | 29.709611 | 0.000001 | 0.000003 |
| 150 | 2025 | 29.745995 | 2025 | 29.745994 | 0.000001 | 0.000002 |
| **200** | **3608** | **29.828123** | **3607** | **29.828210** | **0.000087** | **0.000291** |
| **October** | 50 | 261 | 30.419653 | 261 | 30.419655 | 0.000002 | 0.000007 |
| 75 | 567 | 30.447701 | 567 | 30.447698 | 0.000003 | 0.000008 |
| 100 | 979 | 30.454050 | 979 | 30.454049 | 0.000001 | 0.000003 |
| 125 | 1509 | 30.430580 | 1509 | 30.430579 | 0.000001 | 0.000004 |
| 150 | 2194 | 30.451580 | 2194 | 30.451581 | 0.000001 | 0.000003 |
| **200** | **3886** | **30.522985** | **3885** | **30.523055** | **0.000070** | **0.000228** |
| **November** | 50 | 256 | 28.731289 | 256 | 28.731288 | 0.000001 | 0.000003 |
| 75 | 562 | 28.736244 | 562 | 28.736245 | 0.000001 | 0.000003 |
| 100 | 971 | 28.711998 | 971 | 28.711997 | 0.000001 | 0.000003 |
| 125 | 1513 | 28.706659 | 1513 | 28.706662 | 0.000003 | 0.000009 |
| 150 | 2197 | 28.733824 | 2197 | 28.733823 | 0.000001 | 0.000003 |
| **200** | **3883** | **28.880903** | **3882** | **28.880858** | **0.000045** | **0.000157** |
| **December** | 50 | 251 | 26.793924 | 251 | 26.793924 | 0.000000 | 0.000001 |
| 75 | 557 | 26.988779 | 557 | 26.988779 | 0.000000 | 0.000000 |
| 100 | 970 | 27.111784 | 970 | 27.111783 | 0.000001 | 0.000004 |
| 125 | 1504 | 27.196808 | 1504 | 27.196808 | 0.000000 | 0.000001 |
| 150 | 2174 | 27.301113 | 2174 | 27.301113 | 0.000000 | 0.000000 |
| **200** | **3882** | **27.481401** | **3881** | **27.481333** | **0.000068** | **0.000249** |

**Table 3: Annual 200Km Buffer Analysis**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Month** | **ArcGIS Pixels** | **ArcGIS Mean** | **SeaDAS Pixel** | **SeaDAS Mean** | **Error** | **APE** |
| **January** | 3427 | 26.546511 | 3426 | 26.546393 | 0.000118 | 0.000443 |
| **February** | 3376 | 27.627579 | 3375 | 27.627473 | 0.000106 | 0.000383 |
| **March** | 3327 | 29.003969 | 3326 | 29.003806 | 0.000163 | 0.000563 |
| **April** | 3340 | 30.305183 | 3339 | 30.305252 | 0.000069 | 0.000226 |
| **May** | 3462 | 31.343615 | 3461 | 31.343521 | 0.000094 | 0.000299 |
| **June** | 3456 | 30.579834 | 3455 | 30.579827 | 0.000007 | 0.000023 |
| **July** | 2958 | 28.510481 | 2957 | 28.510366 | 0.000115 | 0.000403 |
| **August** | 3346 | 29.423143 | 3345 | 29.423280 | 0.000137 | 0.000464 |
| **September** | 3608 | 29.828123 | 3607 | 29.828210 | 0.000087 | 0.000291 |
| **October** | 3886 | 30.522985 | 3885 | 30.523055 | 0.000070 | 0.000228 |
| **November** | 3883 | 28.880903 | 3882 | 28.880858 | 0.000045 | 0.000157 |
| **December** | 3882 | 27.481401 | 3881 | 27.481333 | 0.000068 | 0.000249 |

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