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Individual Study : Snee and Zoback (2022) Maximum Horizontal Stress Distribution Data Visualization and Statistical Analyses

Abstract

In this study, the distribution of maximum horizontal stress(Shmax) in areas throughout North America was investigated and visualized using the dataset and article published by Snee and Zoback in 2011. The Snee and Zoback study focuses on significant unconventional oil and gas fields where Shmax has a substantial impact due to Shmax pattern's importance in oil and gas fields can enhance the all stages of the industry, from resource discovery to production. With the help of these parameters, many critical interpretations can be made. These interpretations are used in various analyses and play an important role in the oil and gas industry. Accordingly, the aim of this study is to gain knowledge about the maximum horizontal stress within the study area, understand the major patterns, and identify the rotations in Shmax orientation. For this purpose, the spatial distributions of measurement points and a rose diagram were visualized to better understand the Shmax orientation, and the Shmax-Average Depth relationship was visualized to examine the effect of depth on Shmax. Finally, detailed information was obtained by statistically calculating the parameters.

Introduction

Horizontal maximum stress (Shmax) is the largest compressive stress acting in the horizontal plane within the Earth's crust and is a critical parameter in geomechanics, tectonics, and resource extraction. It is one of the principal stresses, alongside horizontal minimum stress (Shmin) and vertical stress (Sv), which defines the stress state at a given location. Shmax plays a key role in controlling fracture propagation, as new fractures tend to form perpendicular to the minimum stress direction, and it influences fault reactivation and regional tectonic activity. In terms of compressional stress and Shmax, the US Intermountain West is significant due to the complexity of its orientation. There has been an ongoing debate for decades about the orientation of Shmax in this area; while some scientists advocate for a Northeast-Southwest orientation such as Erslev and Larson (2006), others believe in a Southeast-Northwest orientation as discussed by Snee and Zoback (2022). Understanding the orientation of Shmax is essential for the oil and gas industry as it directly impacts exploration, drilling, and production. Hydraulic fractures propagate perpendicular to the minimum horizontal stress (Shmin) and parallel to Shmax, making its orientation crucial for optimizing hydraulic fracturing and maximizing hydrocarbon flow. Proper alignment with Shmax also ensures wellbore stability, reducing risks of collapse and drilling-related issues. Furthermore, Shmax controls the activation and connectivity of natural fracture systems, enhancing reservoir drainage and productivity. It plays a critical role in managing reservoirs and designing enhanced recovery strategies by influencing fracture reactivation and permeability. Additionally, understanding Shmax helps mitigate seismic hazards by avoiding fault reactivation and ensuring safe operations. On a larger scale, Shmax orientation provides insights into tectonic stress regimes, guiding basin-scale exploration and development. For naturally fractured reservoirs, it determines which fractures are open and productive. Ultimately, Shmax orientation is vital for planning well patterns, optimizing lateral placements, and ensuring the economic and operational success of oil and gas projects.

In [1]:
```
#Starting with importing pandas and data set

import pandas as pd

url = 'https://drive.google.com/uc?export=download&id=1Tgs3zrC9aOWm4Fkattsr0D4tndGHkGK-'
data= pd.read_csv(url)
print(data.head())
```

```
     ID  LAT_SURF  LON_SURF   SHMAX_OR1   OR1_SD   SHMIN_OR1 OR1_AV_DEPTH_M  \
0  A427     33.20    -97.20  196.000000      NaN  286.000000            NaN
1  A428     33.20    -97.20  194.000000      NaN  284.000000            NaN
2   A16     32.82    -97.94   47.185900  17.8099  137.185900        1316.12
3  A108     32.67    -97.24   39.319700   5.9346  129.319700        2203.34
4  A111     33.61    -98.03   33.111055   3.3339  123.111056        1986.89

  OR1_QUAL OR1_TYPE OR1_METHOD OR1_NUM_OBS OR1_DATE_OBT  OR1_TOP_M  OR1_BOT_M
0        A      FMF        FMF         247     20170217        NaN        NaN
1        A      FMF        FMF         398     20170217        NaN        NaN
2        B       BO        FMI           7     20170818     1275.9     1492.6
3        A      DIF        FMI          72     20151003     1990.8     2330.2
4        A      DIF        FMI          36     20151003     1641.8     2086.0
```

Data Wrangling

In [2]:
```
import matplotlib.pyplot as plt
import numpy as np

# Dataset is filtered to exclude invalid or missing (NaN) values for the SHMAX_OR1 field, whic
shmax_or1_data = data['SHMAX_OR1'].dropna()

# Stress orientations are converted from degrees to radians using np.radians() because matplo
orientations_rad = np.radians(shmax_or1_data)
```

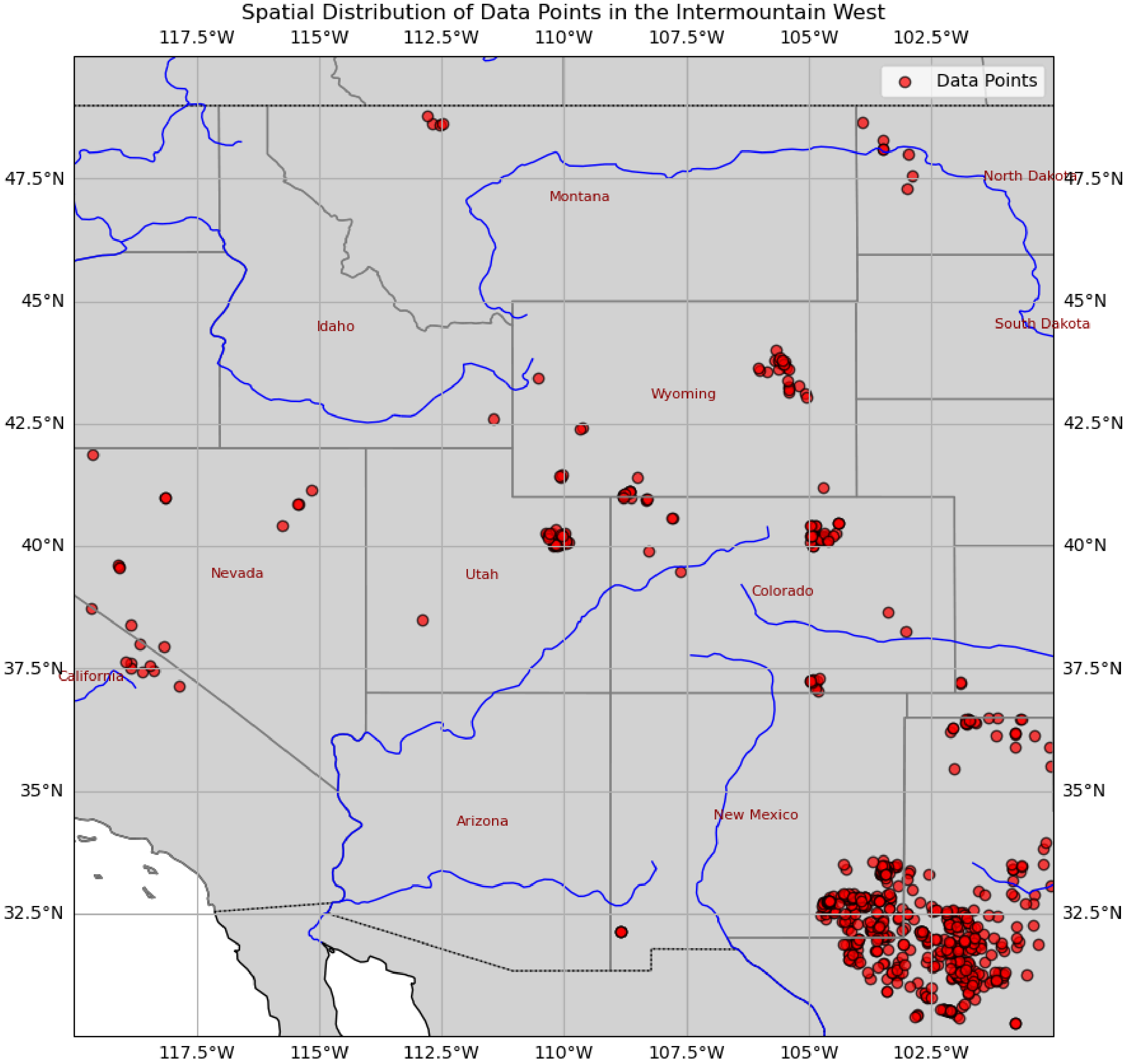
Data Visualization

In this section, the spatial distributions of measurement points and a rose diagram were visualized to better understand the Shmax orientation, and the Shmax-Average Depth relationship was visualized to examine the effect of depth on Shmax.

Spatial Distribution of Data Points

For industries like oil and gas, understanding spatial distributions is key to locating productive regions, optimizing well placements, and improving resource recovery. It also aids in detecting anomalies, such as outliers or unique features, and enhances predictive modeling by improving the accuracy of simulations and interpolations. By linking spatial and temporal trends, it provides a dynamic understanding of changes over time, such as tectonic shifts or reservoir depletion, making it a cornerstone for informed decision-making and scientific exploration.

In [3]:
```
import cartopy.crs as ccrs
import cartopy.feature as cfeature
from cartopy.io.shapereader import natural_earth, Reader

# Extract latitude and longitude data
latitudes = data['LAT_SURF']
longitudes = data['LON_SURF']

# Load state boundaries and names from Natural Earth shapefile
shapefile = natural_earth(resolution='110m', category='cultural', name='admin_1_states_provin
states = Reader(shapefile)

# Create a plot with a basemap
plt.figure(figsize=(12, 10))
ax = plt.axes(projection=ccrs.PlateCarree())

# Add map features
ax.add_feature(cfeature.LAND, edgecolor='black', facecolor='lightgray')
ax.add_feature(cfeature.STATES, edgecolor='gray')  # Add state boundaries
ax.add_feature(cfeature.BORDERS, linestyle=':', edgecolor='black')  # Add country borders
ax.add_feature(cfeature.RIVERS, edgecolor='blue')

# Focus the map on the Intermountain West region
ax.set_extent([-120, -100, 30, 50], crs=ccrs.PlateCarree())

# Add state names to the map
for state_geom, state_info in zip(states.geometries(), states.records()):
    state_name = state_info.attributes['name']  # Extract the state name
    state_centroid = state_geom.centroid  # Get the centroid of the state
    if -120 <= state_centroid.x <= -100 and 30 <= state_centroid.y <= 50:  # Check if within
        ax.text(state_centroid.x, state_centroid.y, state_name,
                transform=ccrs.PlateCarree(), fontsize=8, ha='center', color='darkred')

# Plotting the data points and adding gridlines,legend
plt.scatter(longitudes, latitudes, c='red', alpha=0.7, edgecolors='k', label='Data Points', t

ax.gridlines(draw_labels=True)
plt.title('Spatial Distribution of Data Points in the Intermountain West')
plt.legend()
plt.show()
```

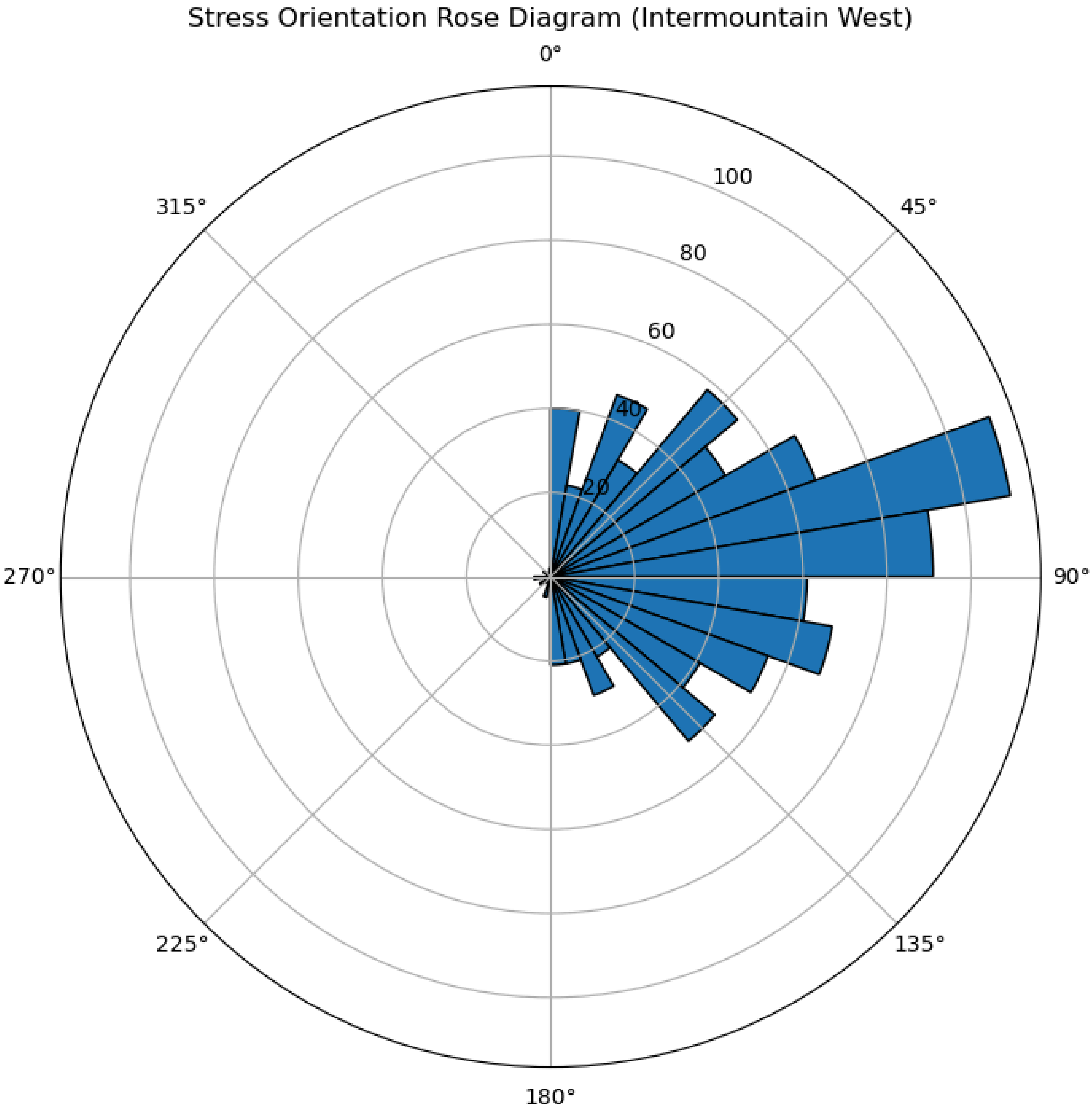


Rose Diagram

A polar plot is created using `matplotlib.pyplot` with the `projection='polar'` argument, where the histogram is visualized as a series of bars arranged in a circular pattern, referred to as a rose diagram. Each bar's height represents the number of stress orientations in a specific angular interval, providing a visual representation of directional data. The `set_theta_zero_location('N')` function sets the zero angle (0°) at the top (north), while `set_theta_direction(-1)` makes the angles increase in a clockwise direction, adhering to the geoscience convention for azimuthal data. This rose diagram clearly visualizes the directional trends of stress orientations in the dataset, allowing geoscientists to easily identify dominant Shmax orientations and their variability. Such insights are crucial for understanding the stress regime in the region. This type of visualization is widely used in structural geology, tectonics, and reservoir engineering to analyze directional data such as fractures, faults, and stress orientations.

In [4]:
```
# Define bounds for the Intermountain West region
min_longitude, max_longitude = -120, -100
min_latitude, max_latitude = 30, 50

# Filter data for the Intermountain West region
filtered_data = data[
```

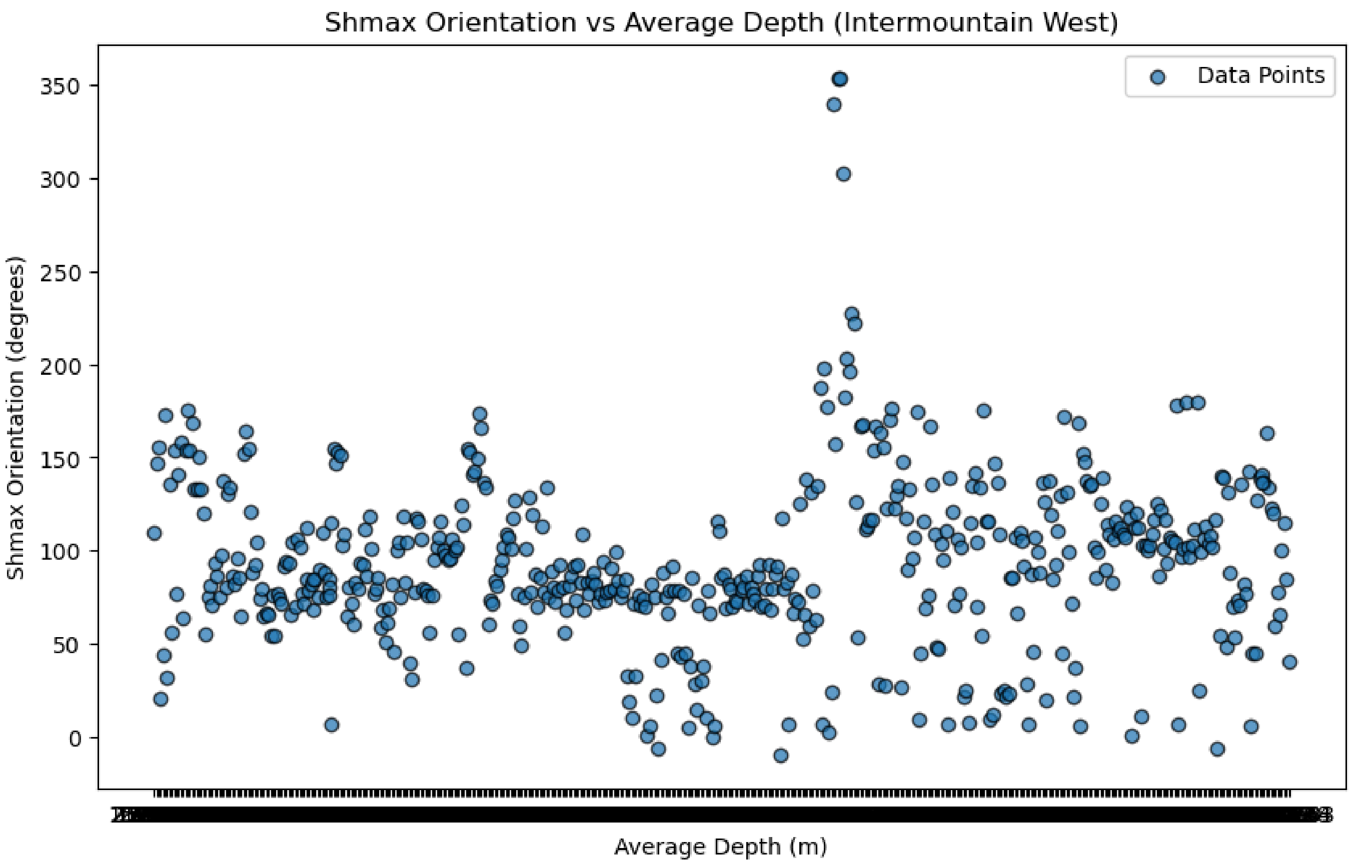
```
    (data['LON_SURF'] >= min_longitude) &
    (data['LON_SURF'] <= max_longitude) &
    (data['LAT_SURF'] >= min_latitude) &
    (data['LAT_SURF'] <= max_latitude)
]

# Create the rose diagram
fig, ax = plt.subplots(subplot_kw={'projection': 'polar'}, figsize=(8, 8))

# Bin the data into 36 bins (10-degree intervals)
n_bins = 36
bin_edges = np.linspace(0, 2 * np.pi, n_bins + 1)

# Create a histogram
hist, _ = np.histogram(orientations_rad, bins=bin_edges)

# Plot the data on the polar chart
ax.bar(bin_edges[:-1], hist, width=2 * np.pi / n_bins, edgecolor='k', align='edge')

# Add labels and title
ax.set_theta_zero_location('N')
ax.set_theta_direction(-1)
ax.set_title('Stress Orientation Rose Diagram (Intermountain West)', va='bottom')

plt.show()
```



Depth-Dependent Stress Regimes

The relationship between average depth and Shmax orientation is crucial in geomechanics, resource exploration, and subsurface engineering, as it provides valuable insights into the stress regime's behavior at different depths. Variations in Shmax orientation with depth can reflect changes in lithology, mechanical properties of rocks, and tectonic forces, helping to understand stress evolution and its impact on faulting and fracture development. This knowledge is essential for predicting fracture propagation, optimizing hydraulic fracturing, and maintaining wellbore stability by avoiding zones where stress shifts could lead to instability. Additionally, it offers tectonic insights into regional stress patterns and fault activity, aiding in seismic hazard assessments. In naturally fractured reservoirs, understanding the Shmax-depth relationship helps identify productive zones by predicting fracture openness and permeability. Furthermore, it enhances predictive modeling of subsurface stress fields, guiding exploration and engineering decisions in data-limited areas. This relationship also plays a critical role in mitigating risks of induced seismicity or fault reactivation, ensuring safer and more efficient resource development.

In [5]:
```
# Define bounds for the Intermountain West region
min_longitude, max_longitude = -120, -100
min_latitude, max_latitude = 30, 50

# Filter data for the Intermountain West region
intermountain_west_data = data[
    (data['LON_SURF'] >= min_longitude) &
    (data['LON_SURF'] <= max_longitude) &
    (data['LAT_SURF'] >= min_latitude) &
    (data['LAT_SURF'] <= max_latitude)
]

# Extract relevant columns and drop rows with missing values
shmax_depth_data_iw = intermountain_west_data[['SHMAX_OR1', 'OR1_AV_DEPTH_M']].dropna()
shmax_or1_iw = shmax_depth_data_iw['SHMAX_OR1']
depth_iw = shmax_depth_data_iw['OR1_AV_DEPTH_M']

# Scatter plot for the Intermountain West region
plt.figure(figsize=(10, 6))
plt.scatter(depth_iw, shmax_or1_iw, alpha=0.7, edgecolors='k', label='Data Points')
plt.title('Shmax Orientation vs Average Depth (Intermountain West)')
plt.xlabel('Average Depth (m)')
plt.ylabel('Shmax Orientation (degrees)')
plt.legend()
plt.show()
```

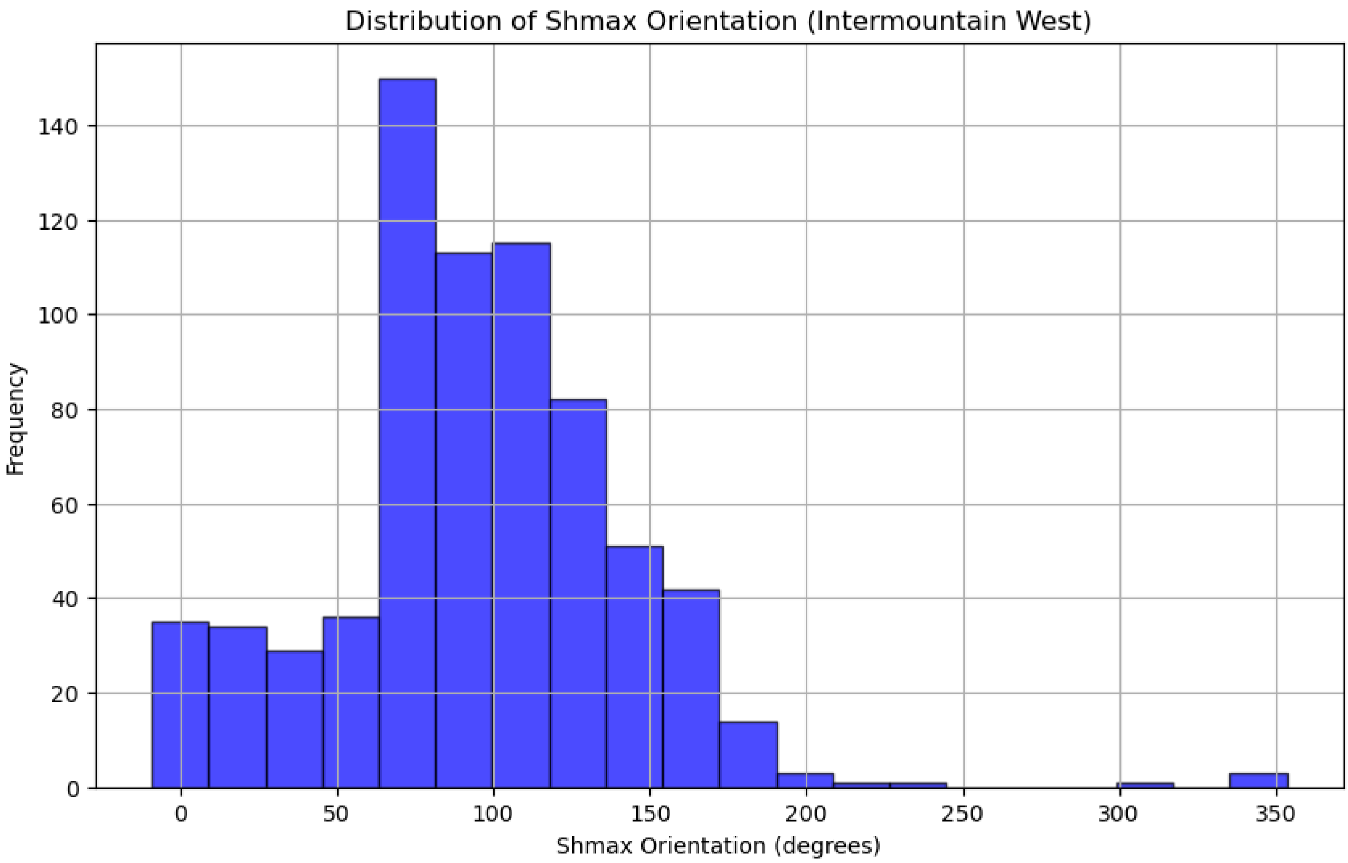


Statistical Analyses

Histogram Plot

The histogram analysis reveals the distribution of Shmax orientations in the Intermountain West region. Most Shmax orientations fall between 50° and 150°, with a clear peak around 50°–100°, indicating a preferred orientation of maximum horizontal stress in the region. This suggests that the regional stress regime is predominantly aligned within this range, which reflects a consistent pattern of tectonic forces acting across the area. The distribution is noticeably skewed, with most orientations concentrated in the lower half of the orientation range (0°–180°) and very few occurrences beyond 180°. This asymmetry may indicate regional tectonic influences or lithological factors that align stress orientations in specific directions. The skewed distribution highlights that the stress regime is not evenly distributed and is shaped by dominant geological forces. Additionally, there are rare or isolated orientations observed in the range of 200°–360°. These could represent local anomalies, unusual tectonic settings, or even data collection inconsistencies. Such outliers might reflect local geological features like minor faults or folds that deviate from the regional trend. In terms of implications, the preferred stress orientations suggest that the region's tectonic stress regime is governed by structural features like fault zones or folds. This understanding can be directly applied in resource exploration and development. By aligning well trajectories or hydraulic fracturing operations with the dominant stress orientations, operators can optimize productivity while avoiding unfavorable stress regimes.

In [6]:
```
# Define bounds for the Intermountain West region
min_longitude, max_longitude = -120, -100
min_latitude, max_latitude = 30, 50

# Filter data for the Intermountain West region
intermountain_west_data = data[
    (data['LON_SURF'] >= min_longitude) &
    (data['LON_SURF'] <= max_longitude) &
    (data['LAT_SURF'] >= min_latitude) &
    (data['LAT_SURF'] <= max_latitude)
]

# Extract SHMAX_OR1 data for the Intermountain West region
shmax_or1_iw = intermountain_west_data['SHMAX_OR1'].dropna()

# Plot the histogram for SHMAX_OR1 (Intermountain West)
plt.figure(figsize=(10, 6))
plt.hist(shmax_or1_iw, bins=20, color='blue', edgecolor='k', alpha=0.7)
plt.title('Distribution of Shmax Orientation (Intermountain West)')
plt.xlabel('Shmax Orientation (degrees)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



Shapiro-Wilk Test for Normality

The Shapiro-Wilk test indicates that the distribution of Shmax orientation (SHMAX_OR1) significantly deviates from normality. This suggests that the data may be influenced by outliers, skewness, or multimodal patterns. As a result, non-parametric methods like Spearman correlation are more appropriate for further analysis

In [7]:
```
from scipy.stats import shapiro, ttest_ind, pearsonr, spearmanr

# Ensure columns are numeric
intermountain_west_data['SHMAX_OR1'] = pd.to_numeric(intermountain_west_data['SHMAX_OR1'], er
intermountain_west_data['OR1_AV_DEPTH_M'] = pd.to_numeric(intermountain_west_data['OR1_AV_DEP

# Filter out rows with missing or non-numeric values
valid_data = intermountain_west_data[['SHMAX_OR1', 'OR1_AV_DEPTH_M']].dropna()

# 1. Shapiro-Wilk Test for Normality on SHMAX_OR1
shapiro_test = shapiro(valid_data['SHMAX_OR1'])
print(f"Shapiro-Wilk Test for SHMAX_OR1:\nStatistic = {shapiro_test.statistic:.4f}, p-value =
```

```
Shapiro-Wilk Test for SHMAX_OR1:
Statistic = 0.9293, p-value = 7.8424e-15
```

```
/tmp/ipykernel_1632/3679431536.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/
indexing.html#returning-a-view-versus-a-copy
  intermountain_west_data['SHMAX_OR1'] = pd.to_numeric(intermountain_west_data['SHMAX_OR1'], e
rrors='coerce')
/tmp/ipykernel_1632/3679431536.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/
indexing.html#returning-a-view-versus-a-copy
  intermountain_west_data['OR1_AV_DEPTH_M'] = pd.to_numeric(intermountain_west_data['OR1_AV_DE
PTH_M'], errors='coerce')
```

Pearson and Spearman Correlations

The Pearson correlation shows a weak positive linear relationship between depth and SHMAX_OR1 (e.g.,r=0.25, r=0.25, p<0.05, p<0.05), suggesting depth has a minor influence on Shmax orientation. However, the Spearman correlation is negligible and not statistically significant, indicating the relationship is not consistently monotonic, potentially due to other influencing factors like lithology or tectonics.

2. Correlation analysis between SHMAX_OR1 and Depth

corr_pearson, p_pearson = pearsonr(valid_data['SHMAX_OR1'], valid_data['OR1_AV_DEPTH_M']) corr_spearman, p_spearman = spearmanr(valid_data['SHMAX_OR1'], valid_data['OR1_AV_DEPTH_M']) print(f"\nPearson Correlation between SHMAX_OR1 and Depth:\nCorrelation = {corr_pearson:.2f}, p-value = {p_pearson:.4e}") print(f"Spearman Correlation between SHMAX_OR1 and Depth:\nCorrelation = {corr_spearman:.2f}, p-value = {p_spearman:.4e}")

Two-Sample t-Test

The t-test reveals a marginally significant difference in mean Shmax orientation between shallow and deep depths (p≈0.05, p≈0.05). This suggests there may be subtle changes in stress orientation with depth, possibly linked to variations in overburden pressure, rock properties, or tectonic forces.

In [9]:
```python
# 3. Two-sample t-test between upper and lower depth ranges
median_depth = valid_data['OR1_AV_DEPTH_M'].median()
upper_depth = valid_data[valid_data['OR1_AV_DEPTH_M'] > median_depth]['SHMAX_OR1']
lower_depth = valid_data[valid_data['OR1_AV_DEPTH_M'] <= median_depth]['SHMAX_OR1']
t_stat, t_pvalue = ttest_ind(upper_depth, lower_depth, equal_var=False)  # Welch's t-test
print(f"\nTwo-Sample t-test for SHMAX_OR1 between Upper and Lower Depth Ranges:\n"
      f"t-statistic = {t_stat:.2f}, p-value = {t_pvalue:.4e}")
```

```
Two-Sample t-test for SHMAX_OR1 between Upper and Lower Depth Ranges:
t-statistic = 1.94, p-value = 5.2470e-02
```

Discussion

The results of this study offer important insights into the stress regime of the Intermountain West region and its relationship with depth. The analysis of Shmax orientations revealed a dominant stress orientation range between **50° and 150°**, with a strong concentration around **50°–100°**. This suggests a prevailing regional tectonic stress pattern, likely influenced by major structural features such as fault zones or folds. However, the skewed distribution and presence of rare orientations in higher ranges (200°–360°) highlight the complexity of the stress regime, which may be shaped by localized geological factors or anomalies. The statistical analyses further support these findings. The weak positive correlation between Shmax orientation and depth (($r = 0.25$)) suggests that depth exerts a minor influence on stress orientation. While the relationship is statistically significant, its strength indicates that other factors, such as lithological variations, fault proximity, or localized tectonic processes, may play a more dominant role. The marginally significant results of the t-test further indicate that there may be subtle differences in stress orientations between shallow and deep depths. These variations could reflect changes in lithology, overburden pressure, or local tectonic forces as depth increases. The non-normal distribution of Shmax orientations, confirmed by the Shapiro-Wilk test, suggests that the stress regime in this region is not uniform. Instead, it may be influenced by a combination of regional tectonic forces and local geological heterogeneity. This emphasizes the importance of employing non-parametric methods like Spearman correlation to capture relationships that may not be strictly linear. These findings have significant implications for geomechanics and resource exploration. The predominant Shmax orientation provides a critical reference for well trajectory planning, hydraulic fracturing design, and resource recovery strategies. For instance, aligning well trajectories with the dominant stress orientations can minimize risks like wellbore instability or drilling-induced fractures. Furthermore, the observed variability in stress orientation with depth underscores the need for depth-specific analyses to optimize operations in complex geological settings. The presence of rare or anomalous orientations raises questions about potential measurement inconsistencies or the influence of unique geological features. Further studies could investigate these outliers in greater detail, possibly incorporating additional datasets or advanced modeling techniques. Incorporating information about lithological variations and fault locations could also enhance the understanding of stress distribution in this region. In summary, while this study provides a robust analysis of Shmax orientations and their depth dependence, it also highlights the complexity of the stress regime in the Intermountain West. Future work should focus on integrating additional geological factors, refining spatial analyses, and employing advanced statistical methods to further unravel the intricate relationships shaping the region's stress field.

Conclusion

This study analyzed the spatial and statistical distribution of Shmax orientations in the Intermountain West region of the US to explore the influence of depth and spatial variability on stress regimes. Using methods from Snee and Zoback (2011), the analysis identified a predominant Shmax orientation range between 50° and 150°, indicating consistent tectonic forces. The skewed distribution and rare orientations in higher ranges (200°–360°) suggest local geological influences or anomalies.Statistical analyses revealed that Shmax orientations deviate from normality, as confirmed by the Shapiro-Wilk test, highlighting the need for non-parametric methods. A weak but significant positive correlation ($r=0.25, p<0.05$r=0.25,p<0.05) between depth and Shmax orientation suggests depth plays a minor role. The t-test results showed marginal differences in orientations between shallow and deep depths ($p\approx0.05$p≈0.05), hinting at subtle stress regime changes due to lithological or tectonic factors.These findings are critical for geomechanical applications, offering insights for optimizing well trajectories and hydraulic fracturing while mitigating risks like wellbore instability. The study underscores the importance of integrating spatial and statistical analyses to interpret stress regimes, aiding in resource exploration and decision-making in complex geological settings.

```
In [ ]:
```