EDA

July 21, 2025

1 COVID-19 County-Level Case Analysis

Exploratory Data Analysis Report
Prepared by: Navid Bahadorn
Date: June, 2025

This report presents a preliminary analysis of COVID-19 county-level case data in the United States, including spatial and temporal trends.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from config import config
import torch

sns.set(style="whitegrid")
pd.set_option('display.max_columns', 100)
```

1.0.1 1. Dataset Summary

We first look at the dimensions and basic statistics of the dataset.

[2]:
```
data_path = config["data_path"]
df = pd.read_csv(data_path)

# Restore dates from "t"
start_date = datetime(2020, 1, 21)
df["date"] = pd.to_datetime(df["t"], unit="D", origin=start_date)

print("Loaded shape:", df.shape)
display(df.head())
print(df.info())
```

```
Loaded shape: (2409352, 5)

          lon        lat   t          u       date
0 -164.040108  64.942121  85  10.167768 2020-04-15
1 -164.040108  64.942121  86  10.167768 2020-04-16
```

```
2 -164.040108  64.942121  87  10.167768 2020-04-17
3 -164.040108  64.942121  88  10.167768 2020-04-18
4 -164.040108  64.942121  89  10.167768 2020-04-19
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2409352 entries, 0 to 2409351
Data columns (total 5 columns):
 #   Column  Dtype
---  ------  -----
 0   lon     float64
 1   lat     float64
 2   t       int64
 3   u       float64
 4   date    datetime64[ns]
dtypes: datetime64[ns](1), float64(3), int64(1)
memory usage: 91.9 MB
None
```

1.0.2 2. Summary Statistics & Nulls

[3]:
```
print("Summary Statistics:")
display(df.describe())

print("Null Value Check:")
print(df.isnull().sum())
```

```
Summary Statistics:

                lon           lat             t             u  \
count  2.409352e+06  2.409352e+06  2.409352e+06  2.409352e+06
mean  -9.214093e+01  3.838049e+01  4.573247e+02  1.011351e+04
min   -1.640401e+02  1.960199e+01  0.000000e+00  1.028686e-02
25%   -9.808979e+01  3.464985e+01  2.650000e+02  2.138229e+03
50%   -9.024324e+01  3.832408e+01  4.580000e+02  9.257088e+03
75%   -8.343685e+01  4.174292e+01  6.510000e+02  1.522107e+04
max   -6.762834e+01  6.935328e+01  8.430000e+02  3.843137e+05
std    1.261735e+01  5.230411e+00  2.235216e+02  8.760030e+03


                                date
count                        2409352
mean   2021-04-22 07:47:36.891645440
min              2020-01-21 00:00:00
25%              2020-10-12 00:00:00
50%              2021-04-23 00:00:00
75%              2021-11-02 00:00:00
max              2022-05-13 00:00:00
std                              NaN

Null Value Check:
```

```
lon     0
lat     0
t       0
u       0
date    0
dtype: int64
```

1.0.3 3.Unique Locations & Data Coverage

[5]:
```
print(f"Unique locations (lon, lat): {df[['lon','lat']].drop_duplicates().
↪shape[0]}")
print(f"Time Range: {df['date'].min().date()} to {df['date'].max().date()}")
```

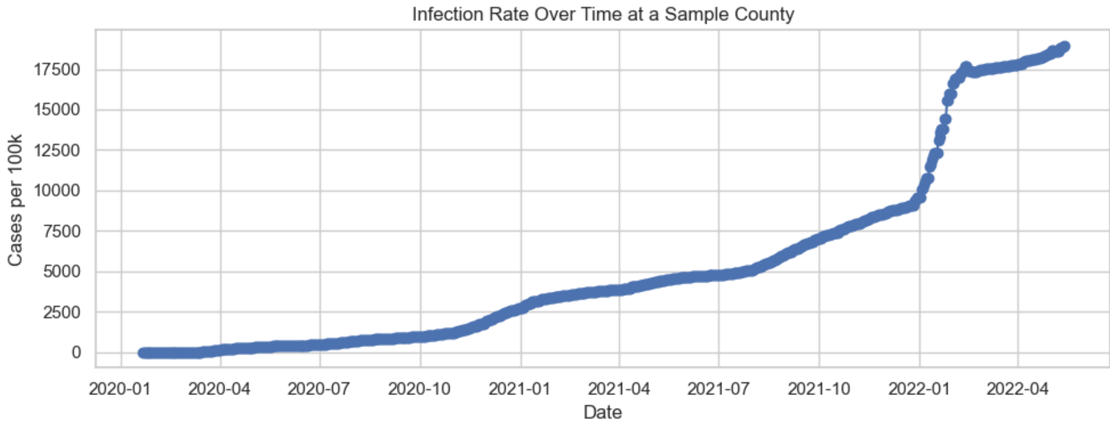
```
Unique locations (lon, lat): 3124
Time Range: 2020-01-21 to 2022-05-13
```

Observation:
The dataset includes infection rate per 100,000 people (`u`) over time for each U.S. county. The data ranges from Jan 2020 onwards and appears to be normalized by population.

1.0.4 4.Sample Time Series for a Random or Top County

We examine the infection trend over time for a sample location with the most data points.

[6]:
```
loc = df.groupby(["lon", "lat"]).size().sort_values(ascending=False).index[0]
df_sample = df[(df["lon"] == loc[0]) & (df["lat"] == loc[1])]

plt.figure(figsize=(10, 4))
plt.plot(df_sample["date"], df_sample["u"], marker="o")
plt.title("Infection Rate Over Time at a Sample County")
plt.xlabel("Date")
plt.ylabel("Cases per 100k")
plt.grid(True)
plt.tight_layout()
plt.show()
```

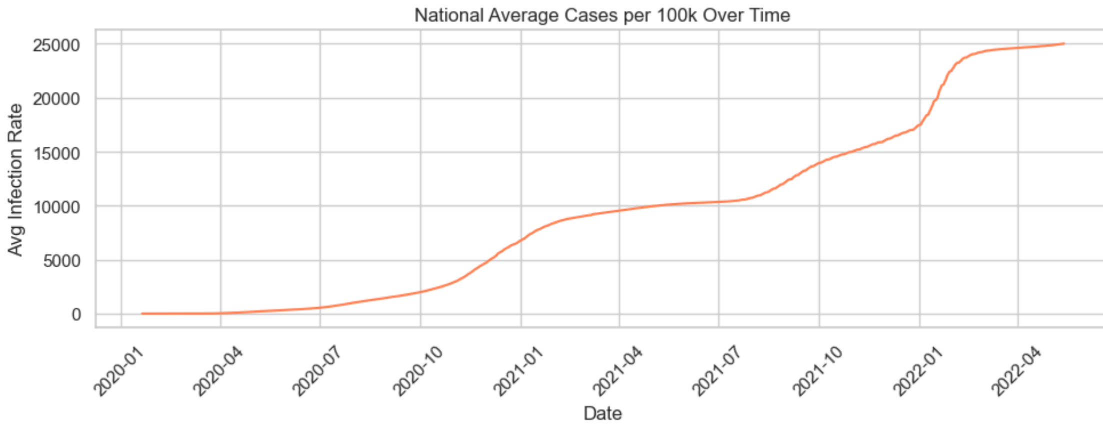


Analysis:
This county shows distinct surges during known COVID waves (e.g., early 2021, late 2021/Omicron). The infection rate exhibits strong temporal spikes followed by rapid declines, consistent with public health intervention cycles.

1.0.5 5. National Average Trend

Here, we analyze the average infection rate across all counties each day.

[7]:
```
df_national = df.groupby("date")["u"].mean().reset_index()

plt.figure(figsize=(10, 4))
sns.lineplot(data=df_national, x="date", y="u", color="coral")
plt.title("National Average Cases per 100k Over Time")
plt.xlabel("Date")
plt.ylabel("Avg Infection Rate")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```

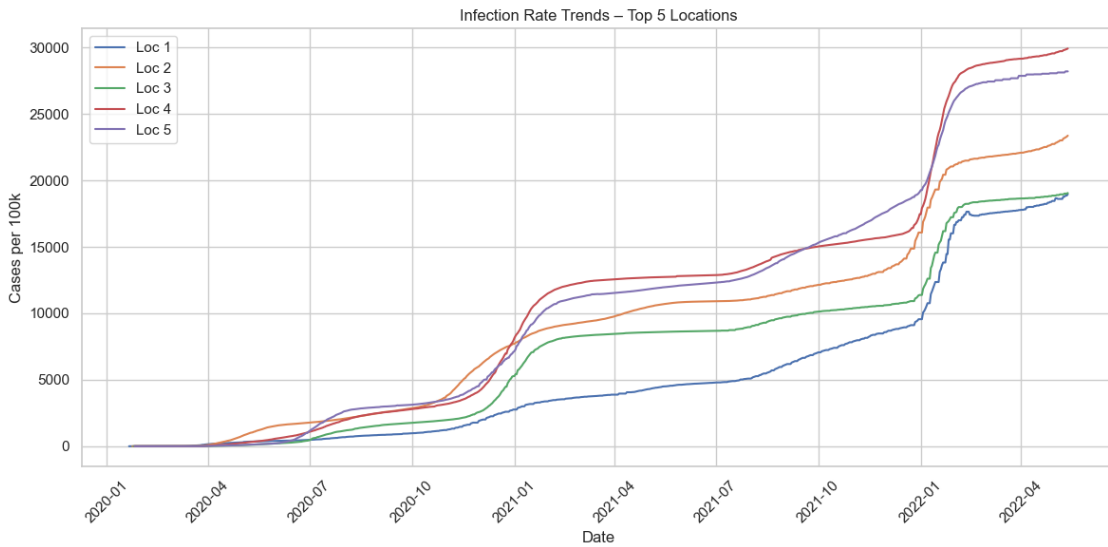


Analysis:
National averages smooth out county-level noise and highlight broad pandemic waves. The three major surges are clearly visible, corresponding to initial outbreak, Delta, and Omicron waves.

1.0.6 6. Heatmap: Top Locations

We now plot trends for the top 5 counties by data density.

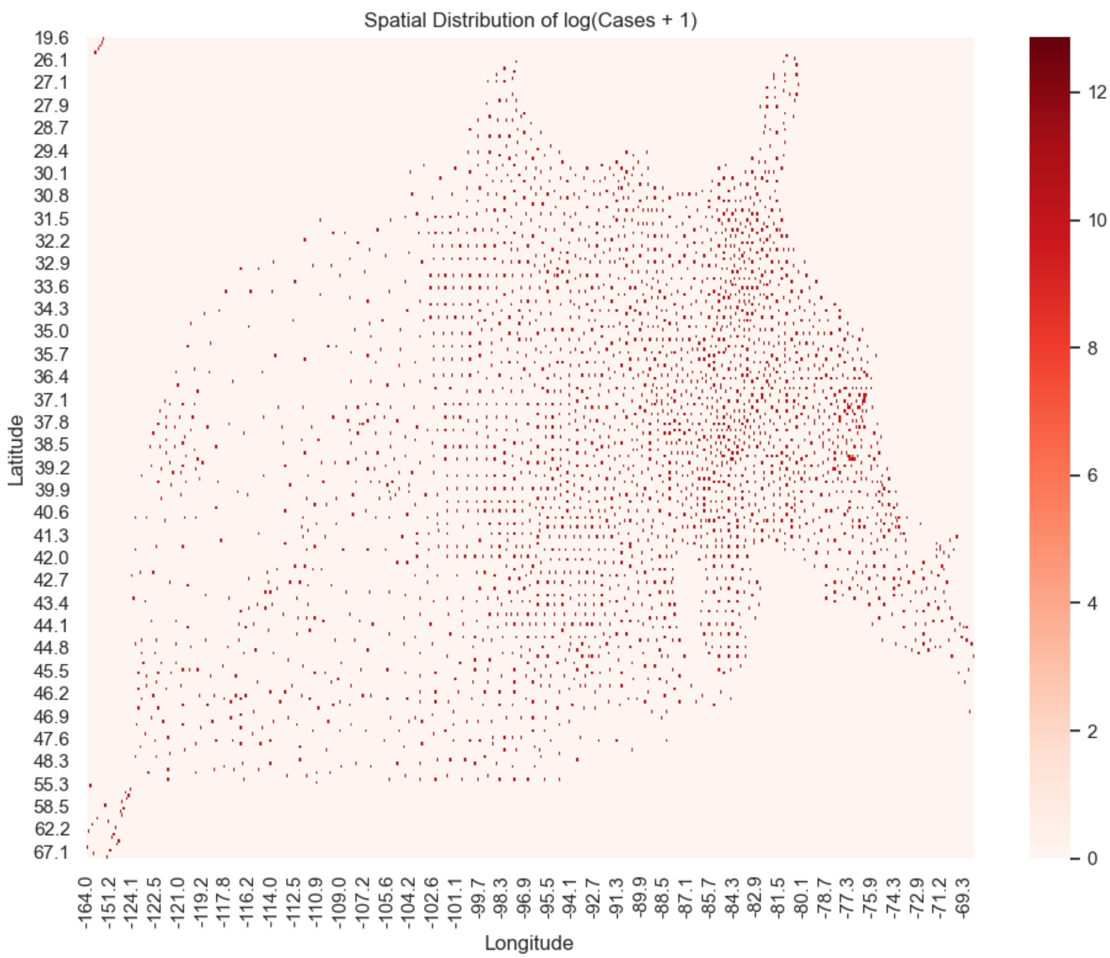
[8]:
```
# Get top 5 locations with most records
top5_locs = df.groupby(["lon", "lat"]).size().sort_values(ascending=False).
  ↪head(5).index

# Plot time series for each
plt.figure(figsize=(12, 6))
for i, loc in enumerate(top5_locs):
    df_sub = df[(df["lon"] == loc[0]) & (df["lat"] == loc[1])]
    plt.plot(df_sub["date"], df_sub["u"], label=f"Loc {i+1}")
plt.legend()
plt.title("Infection Rate Trends - Top 5 Locations")
plt.xlabel("Date")
plt.ylabel("Cases per 100k")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Analysis:
Comparing different counties reveals variations in timing and magnitude of infection waves. Some counties show delayed or prolonged peaks, possibly due to differences in population density, interventions, or mobility.

1.0.7 Heatmap of a specific time slice

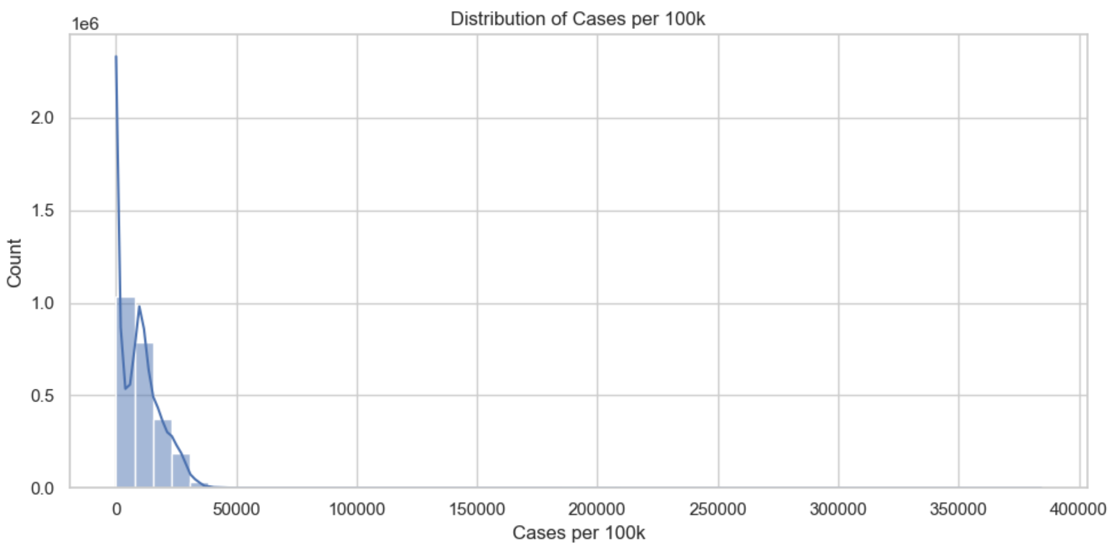
[7]:
```
df_t = df[df["t"] == df["t"].max()].copy()
df_t["lat_round"] = df_t["lat"].round(1)
df_t["lon_round"] = df_t["lon"].round(1)

heatmap_data = df_t.pivot_table(index="lat_round", columns="lon_round",␣
 ↪values="u", aggfunc="mean")
heatmap_data = heatmap_data.fillna(0)

# Optionally log-scale for visualization
plt.figure(figsize=(10, 8))
sns.heatmap(np.log1p(heatmap_data), cmap="Reds")
plt.title("Spatial Distribution of log(Cases + 1)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.tight_layout()
plt.show()
```



1.0.8 7.Daily Histogram of Cases per 100k

Next, we examine how infection rates are distributed overall.

[23]:
```
plt.figure(figsize=(10, 5))
sns.histplot(df["u"], bins=50, kde=True)
plt.title("Distribution of Cases per 100k")
plt.xlabel("Cases per 100k")
plt.tight_layout()
plt.show()
```

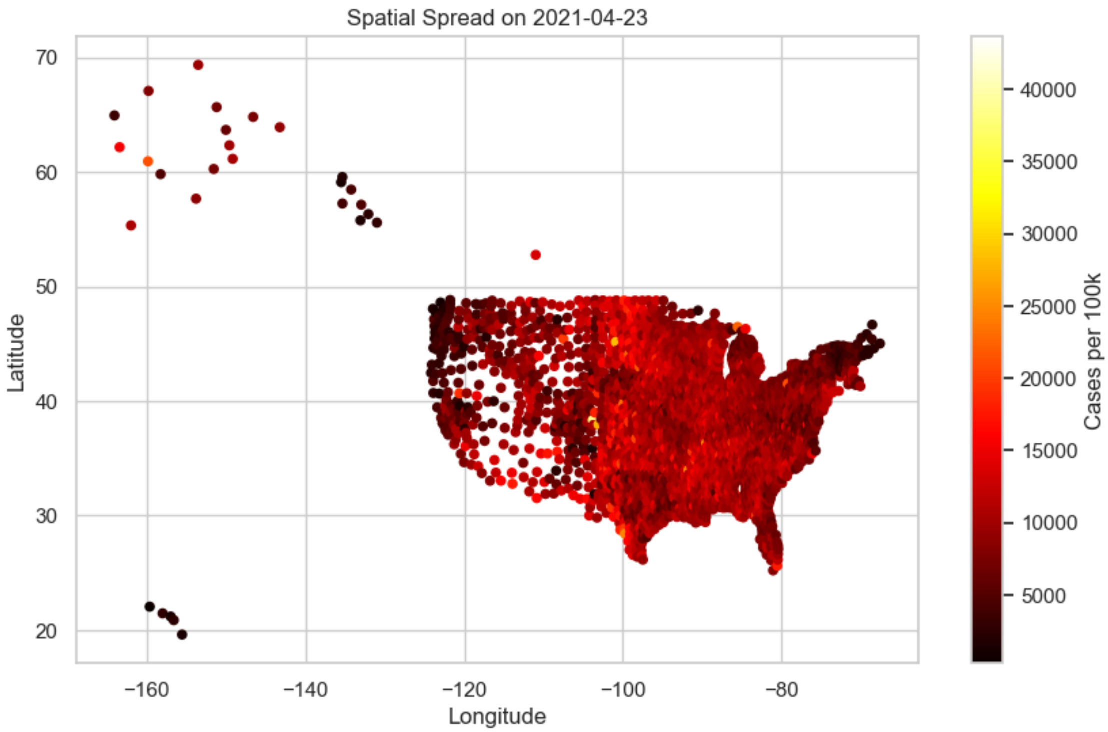


Analysis:
The distribution is right-skewed, with a long tail of counties experiencing very high infection rates. Most data points fall below 500 per 100k.

1.0.9 8.Geographic Snapshots for a Specific Date

We visualize the infection rate across counties on a single median day.

[25]:
```
# Pick a snapshot day (e.g., peak period)
snapshot_day = df["date"].median()
df_day = df[df["date"] == snapshot_day]

plt.figure(figsize=(10, 6))
plt.scatter(df_day["lon"], df_day["lat"], c=df_day["u"], cmap="hot", s=20)
plt.colorbar(label="Cases per 100k")
plt.title(f"Spatial Spread on {snapshot_day.date()}")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.grid(True)
plt.show()
```

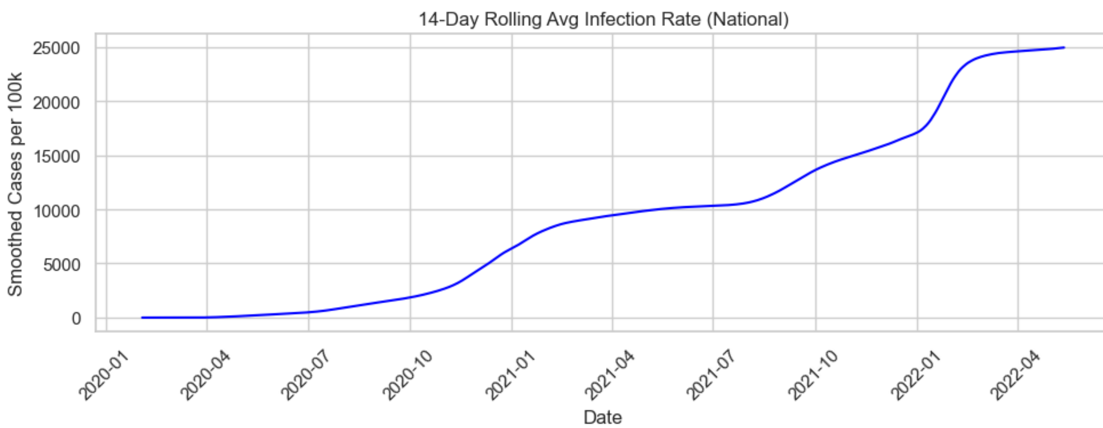


Analysis:
Geographic variation in infection intensity is clearly visible. Certain hotspots are evident, possibly urban centers. This spatial map offers a useful way to model regional dynamics later.

1.0.10 9.Rolling Average

This smooths daily noise and captures trends.

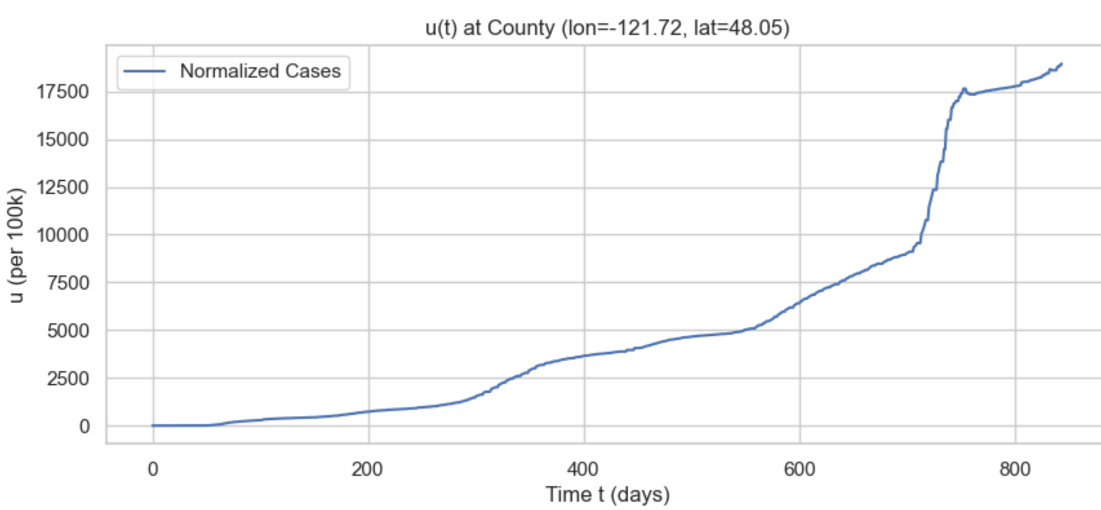
[26]:
```
df_rolling = df.groupby("date")["u"].mean().rolling(window=14).mean().
 ↪reset_index()

plt.figure(figsize=(10, 4))
sns.lineplot(data=df_rolling, x="date", y="u", color="blue")
plt.title("14-Day Rolling Avg Infection Rate (National)")
plt.xlabel("Date")
plt.ylabel("Smoothed Cases per 100k")
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.show()
```



Analysis:
This plot smooths out day-to-day volatility, showing the three major pandemic phases with clear transitions and drop-offs. This can help guide training windows for time-series models.

---

[27]:
```python
# Pick a random location
sample = df.groupby(["lon", "lat"]).size().sort_values(ascending=False).index[0]
df_sample = df[(df["lon"] == sample[0]) & (df["lat"] == sample[1])]

plt.figure(figsize=(10, 4))
plt.plot(df_sample["t"], df_sample["u"], label="Normalized Cases")
plt.title(f"u(t) at County (lon={sample[0]:.2f}, lat={sample[1]:.2f})")
plt.xlabel("Time t (days)"); plt.ylabel("u (per 100k)")
plt.grid(True)
plt.legend()
plt.show()
```



1.0.11 Conclusions

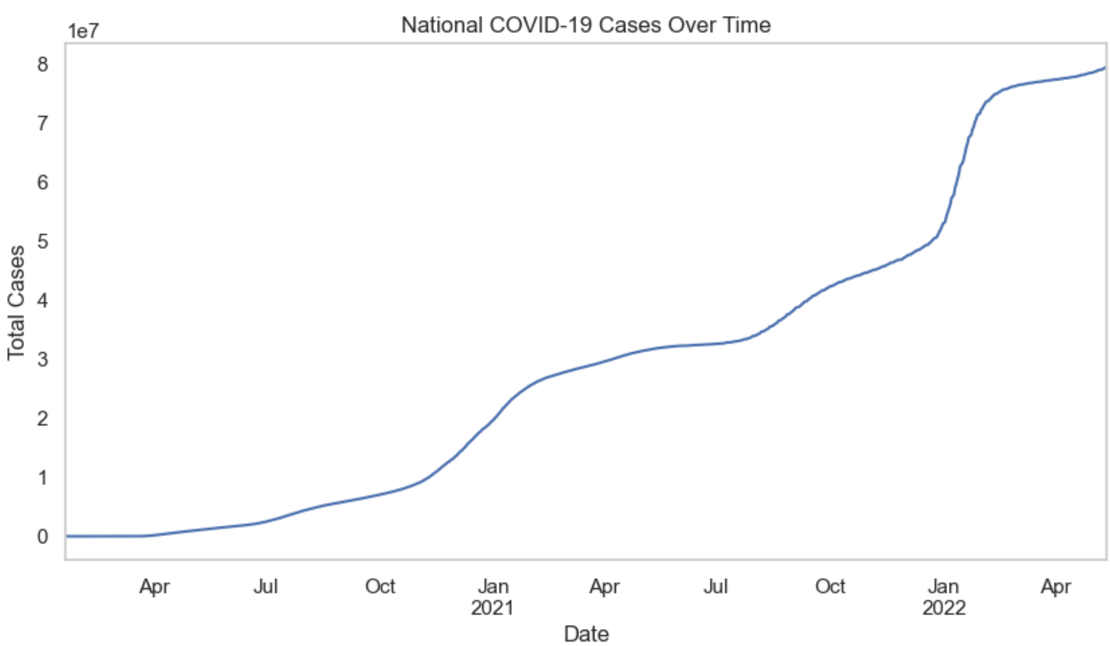
- Temporal trends align with known pandemic waves.
- Spatial variation suggests that geographic modeling is necessary.
- Rolling averages are essential to suppress noise in training data.

This analysis supports using Physics-Informed Neural Networks (PINNs) with both spatial and temporal inputs for modeling spread dynamics.

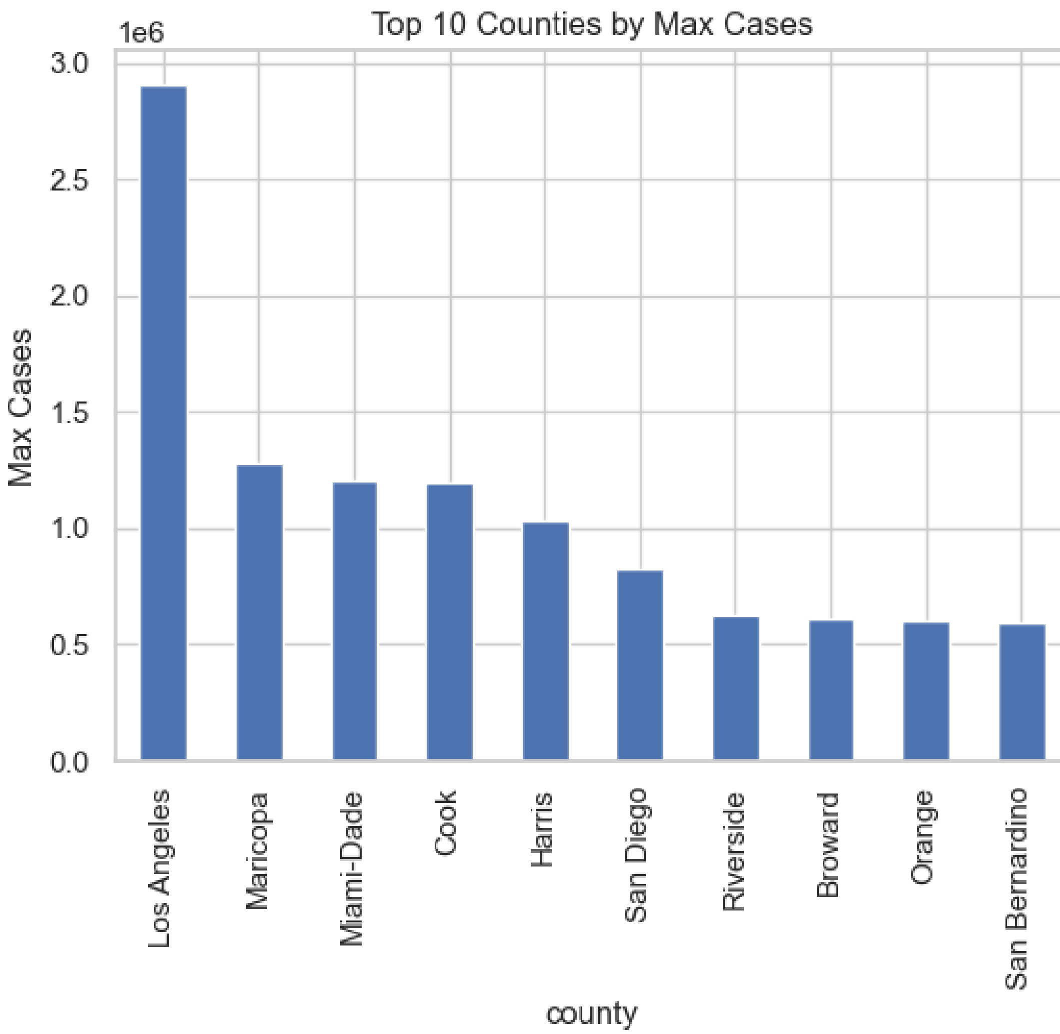
---

[29]:
```
# Convert date
df["date"] = pd.to_datetime(df["date"])
```

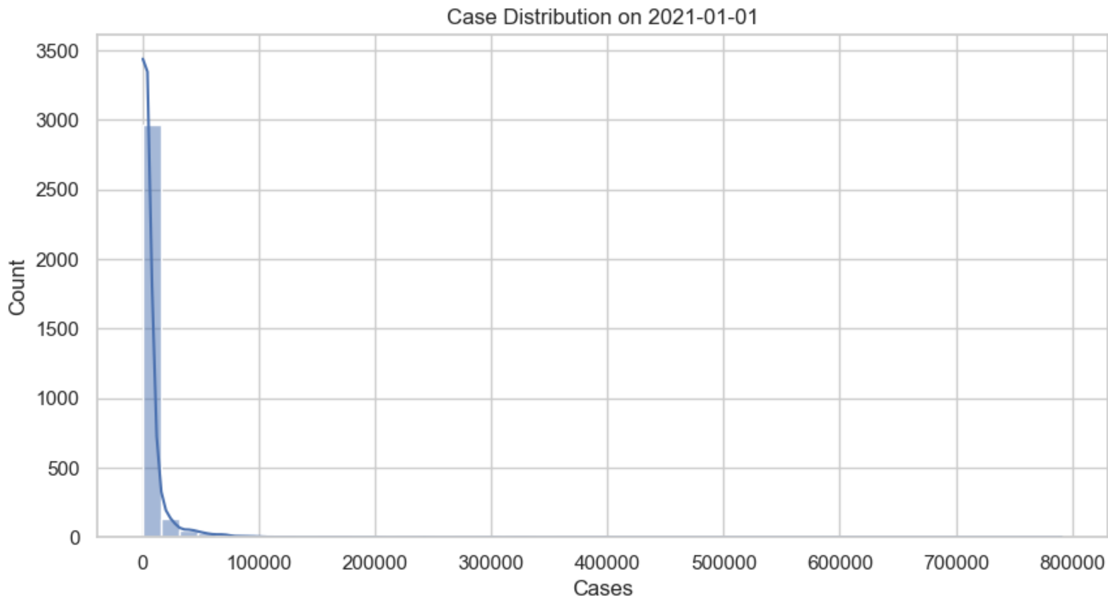
[30]:
```
# Total cases over time (U.S.)
national_cases = df.groupby("date")["cases"].sum()
plt.figure(figsize=(10, 5))
national_cases.plot(title="National COVID-19 Cases Over Time")
plt.xlabel("Date")
plt.ylabel("Total Cases")
plt.grid()
plt.show()
```



```
[31]: # Top 10 counties by total cases
top_counties = df.groupby("county")["cases"].max().nlargest(10)
top_counties.plot(kind="bar", title="Top 10 Counties by Max Cases")
plt.ylabel("Max Cases")
plt.show()
```




```
[32]: # Cases heatmap: example on a single date
single_day = df[df["date"] == "2021-01-01"]
pivot = single_day.pivot_table(index="fips", values="cases")
plt.figure(figsize=(10, 5))
sns.histplot(single_day["cases"], bins=50, kde=True)
plt.title("Case Distribution on 2021-01-01")
plt.xlabel("Cases")
plt.show()
```

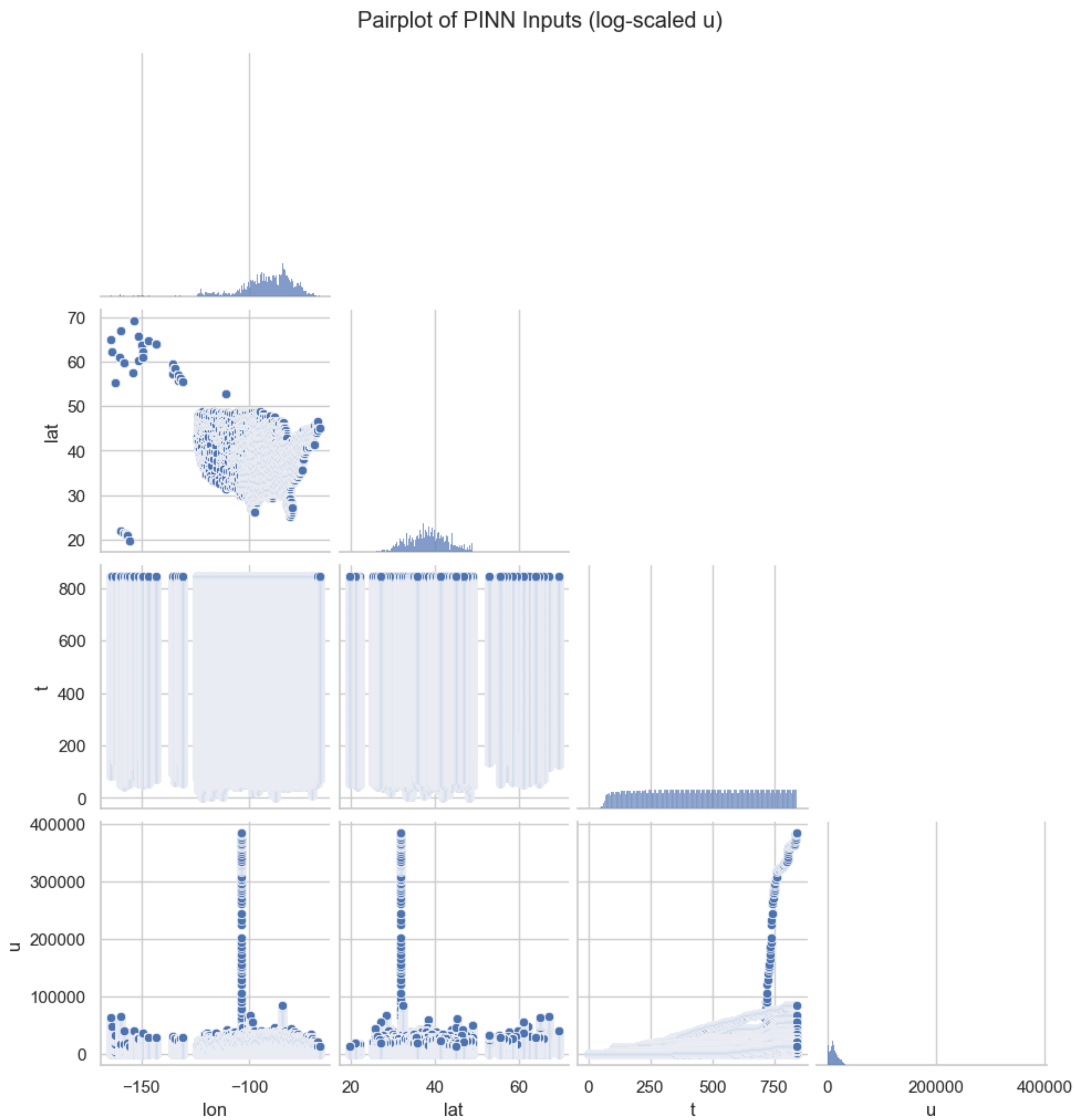


[33]:

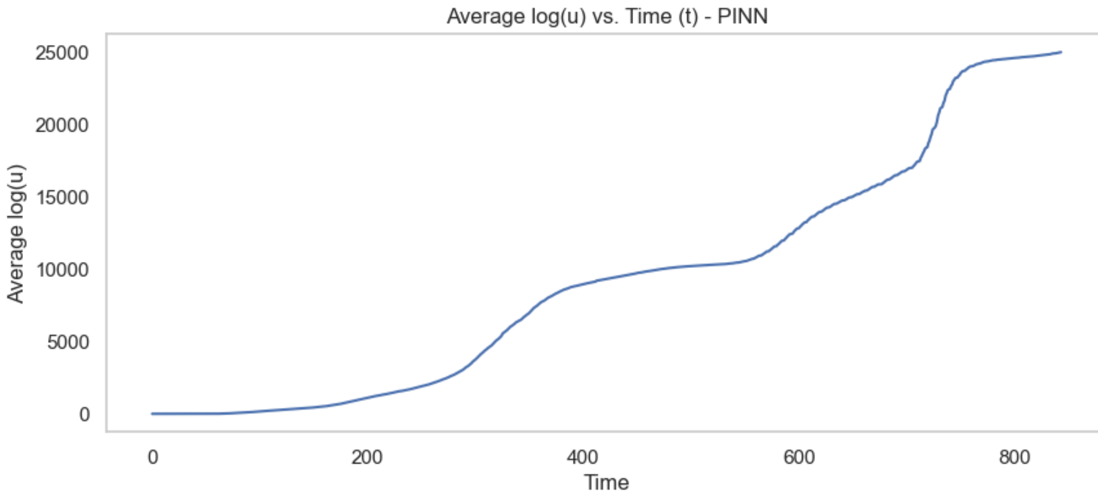
```python
data_path = config["data_path"]
pinn_df = pd.read_csv(data_path)

print("[INFO] PINN Dataset Summary")
display(pinn_df.describe())

# Pairplot of inputs
sns.pairplot(pinn_df[["lon", "lat", "t", "u"]], corner=True)
plt.suptitle("Pairplot of PINN Inputs (log-scaled u)", y=1.02)
plt.show()
```

```
[INFO] PINN Dataset Summary
```

	lon	lat	t	u
count	2.409352e+06	2.409352e+06	2.409352e+06	2.409352e+06
mean	-9.214093e+01	3.838049e+01	4.573247e+02	1.011351e+04
std	1.261735e+01	5.230411e+00	2.235216e+02	8.760030e+03
min	-1.640401e+02	1.960199e+01	0.000000e+00	1.028686e-02
25%	-9.808979e+01	3.464985e+01	2.650000e+02	2.138229e+03
50%	-9.024324e+01	3.832408e+01	4.580000e+02	9.257088e+03
75%	-8.343685e+01	4.174292e+01	6.510000e+02	1.522107e+04
max	-6.762834e+01	6.935328e+01	8.430000e+02	3.843137e+05



[36]:
```
# Time series average
avg_u_time = pinn_df.groupby("t")["u"].mean()
plt.figure(figsize=(10, 4))
avg_u_time.plot()
plt.title("Average log(u) vs. Time (t) - PINN")
plt.xlabel("Time")
plt.ylabel("Average log(u)")
plt.grid()
plt.show()
```



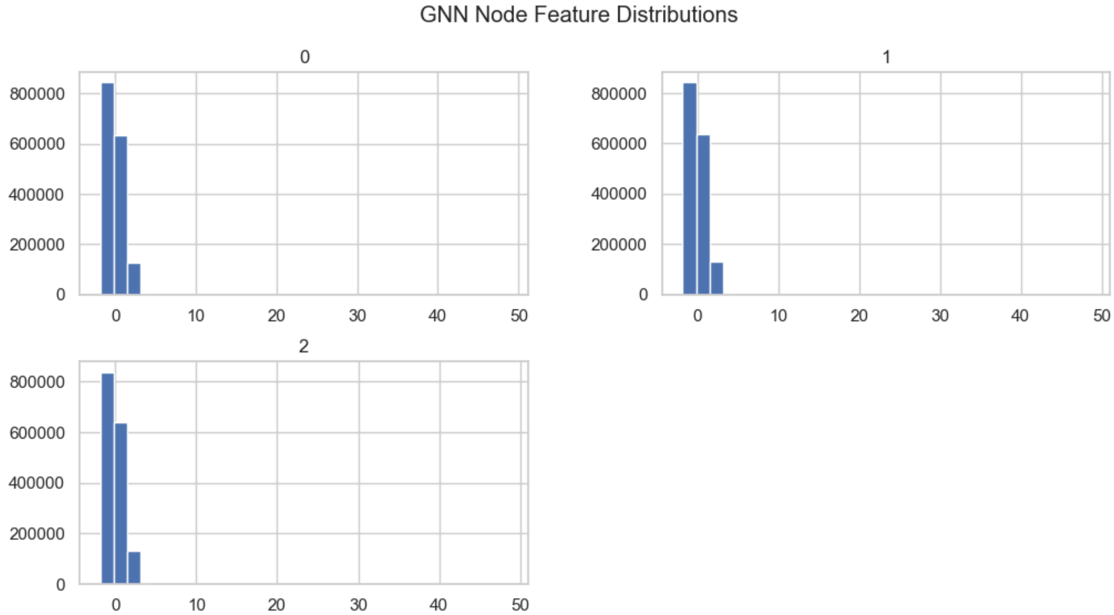
[40]:
```
# Unpack
graph_dataset, node_positions = torch.load(config["gnn_dataset_path"],␣
↪weights_only=False)

print(f"[INFO] Loaded {len(graph_dataset)} graph snapshots.")

# Access first graph snapshot
first_graph = graph_dataset[0]

# EDA
num_nodes = first_graph.num_nodes
num_edges = first_graph.edge_index.shape[1]
avg_deg = num_edges / num_nodes

print(f" GNN Graph Summary:")
print(f"  • Nodes: {num_nodes}")
print(f"  • Edges: {num_edges}")
print(f"  • Avg Degree: {avg_deg:.2f}")
```

```
[INFO] Loaded 516 graph snapshots.
 GNN Graph Summary:
  • Nodes: 3124
  • Edges: 10410
  • Avg Degree: 3.33
```

[41]:
```
# Feature & target stats
x_all = torch.cat([g.x for g in graph_dataset], dim=0).numpy()
y_all = torch.cat([g.y for g in graph_dataset], dim=0).numpy()
```

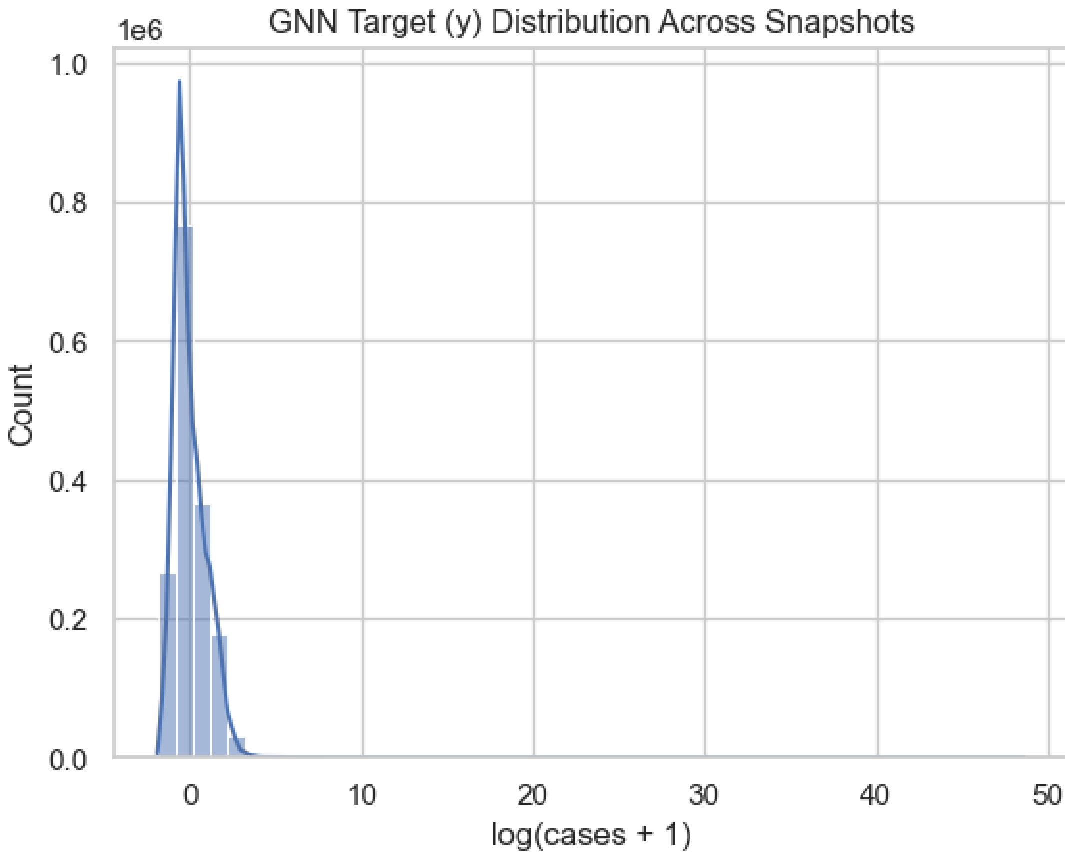
[42]:

```
# Node feature histogram
pd.DataFrame(x_all).hist(bins=30, figsize=(12, 6))
plt.suptitle("GNN Node Feature Distributions")
plt.show()
```

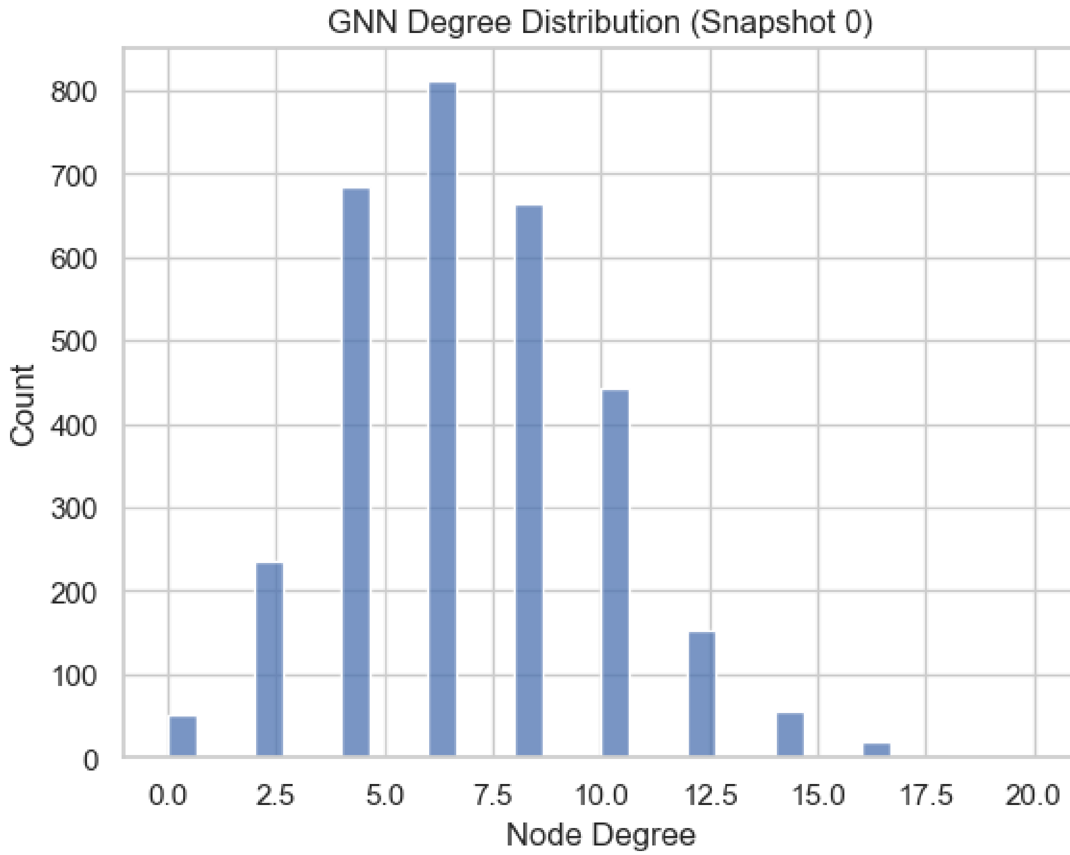


[43]:

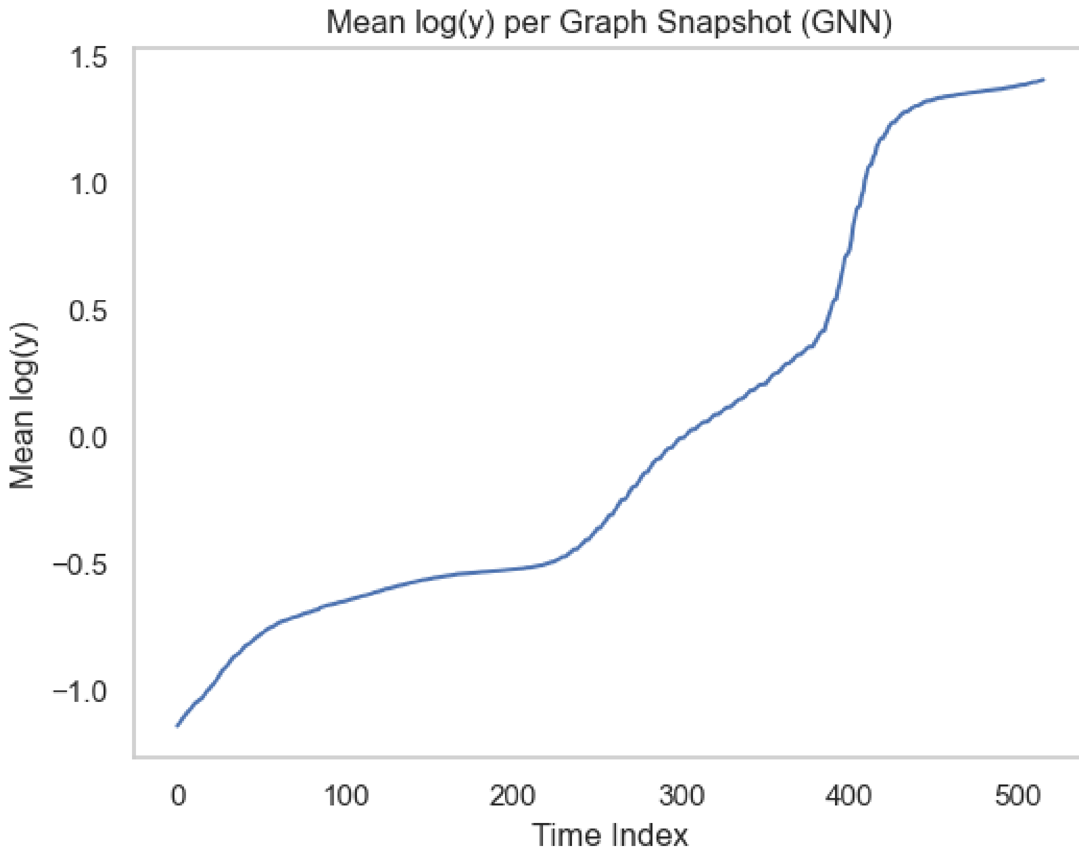
```
# Target histogram
sns.histplot(y_all, bins=50, kde=True)
plt.title("GNN Target (y) Distribution Across Snapshots")
plt.xlabel("log(cases + 1)")
plt.show()
```



[44]:
```
# Degree distribution of a snapshot
from torch_geometric.utils import to_networkx
import networkx as nx

G = to_networkx(graph_dataset[0])
degrees = [deg for _, deg in G.degree()]
sns.histplot(degrees, bins=30)
plt.title("GNN Degree Distribution (Snapshot 0)")
plt.xlabel("Node Degree")
plt.ylabel("Count")
plt.show()
```



[45]:
```python
# Time slice trends (target mean over snapshots)
y_per_snapshot = [g.y.mean().item() for g in graph_dataset]
plt.plot(range(len(graph_dataset)), y_per_snapshot)
plt.title("Mean log(y) per Graph Snapshot (GNN)")
plt.xlabel("Time Index")
plt.ylabel("Mean log(y)")
plt.grid()
plt.show()
```



Mean log(y) per Graph Snapshot (GNN)
1.5
1.0
0.5
0.0
−0.5
−1.0
Mean log(y)
0
100
200
300
400
500
Time Index