It is a nice work to show performance comparison of non-linear dimensionality reduction methods versus PCA.

The attached results given by PCA, LLE and tSNE may vary based on many reasons. PCA (Linear) methods usually works well considering linear projection of the data, but often miss important non-linear structure in the data. LLE and tSNE generalize linear frameworks like PCA to be more sensitive to non-linear structure in data. Generally, tSNE outperforms other methods due to ability to group samples based on the local structure to visually disentangle a dataset that comprises several manifolds at once as like in case of this dataset. This is because a linear method such as PCA is not good at modeling curved manifolds. It focuses on preserving the distances between widely separated data points rather than on preserving the distances between nearby data points.

It seems tSNE didn’t perform good in grouping the seasons in this dataset. I guess scaling of feature might be the cause. Make sure the same scale is used over all features because LLE and tSNE are based on a nearest-neighbor search and may perform poorly. Try normalizing the dataset using MinMaxScaler or StandardScaler and then apply these methods.

Overall, Its good dig out into these dimensionality reduction methods.

You may find more interesting details about these methods here :

<https://www.analyticsvidhya.com/blog/2017/01/t-sne-implementation-r-python/>

<https://scikit-learn.org/stable/modules/manifold.html>

NOTE:

*What is a manifold?*

*The simplest example is our planet Earth. For us it looks flat, but it reality it's a sphere. So it's sort of a 2d manifold embedded in the 3d space*.