Machine Learning for Earth System Sciences
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Module - 01
Spatio - Temporal Statistics
Lecture - 08
Causality

Hello everyone. Welcome to lecture 8 of this course on Machine Learning for Earth System Science. We are still in the 1st module of Spatio-Temporal Statistics and in today's lecture we will deal with the topic of Causality.

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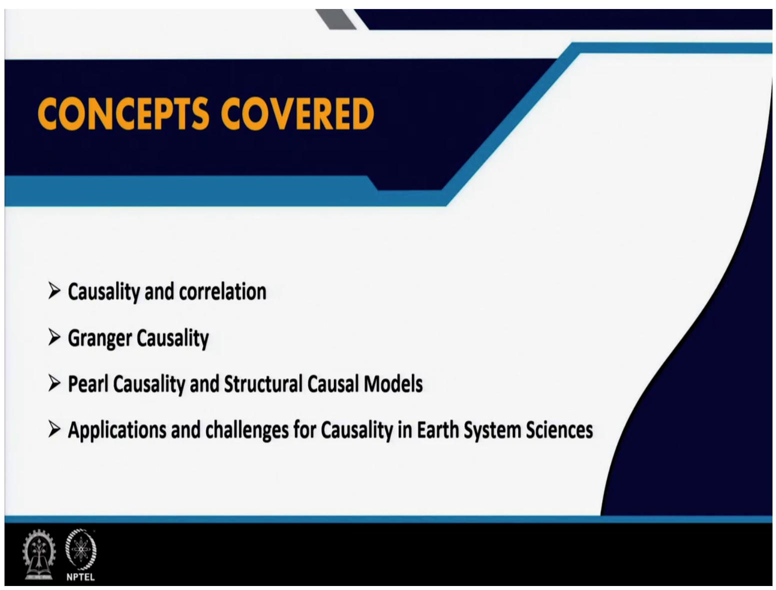

Now, the concepts we will are going to cover today are causality and correlation, granger causality, pearl causality and structural causal models and finally, various applications of causality in earth system sciences and the various challenges involved.

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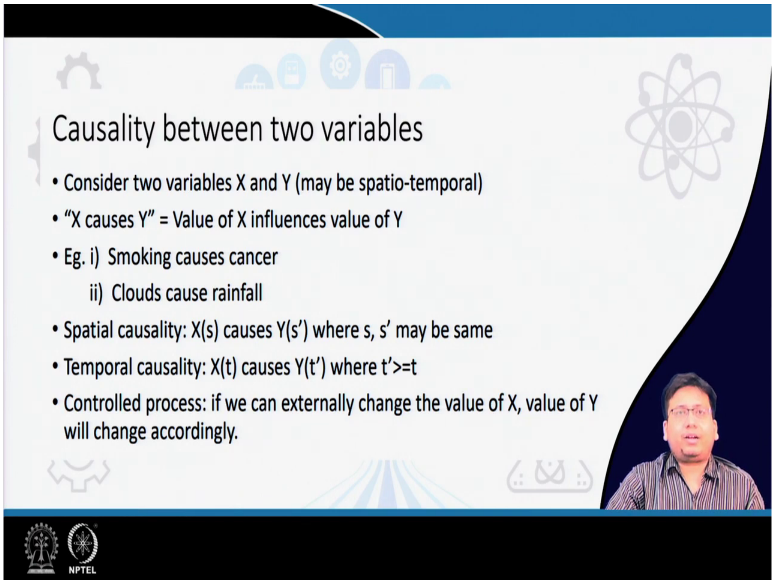

So, first coming to the basic idea of causality let us say that we have two variables X and Y, these variables may be spatio-temporal also. Now the question is when can we say that like one variable causes the other that is one is the cause the other is the effect. So, like basically we are try somehow trying to influence or measure the influence of one variable on the other. Say for example, if we consider two statements like a smoking causes cancer and clouds cause rainfall.

So, like we can measure whether different people smoke or not and we can also measure whether different people have cancer or not. Now on the basis of this data can we a say that for those people who have cancer a like we can say that it is because of the smoking or alternatively can we say that if someone smokes then that automatically means that they have a high risk of cancer or they may have there is a probability that they will get cancer.

So, the similar thing can be said in the other example also. So, whether these kinds of statements we can make or not depends on first of all we have we need to have data and secondly, we need to formulate the questions in an appropriate mathematical language using some probability or some suitable construct like that.

Now, like again in the spatio spatial and temporal causes in the cause a like for in the spatio-temporal domain we can define causality as like both spatial causality and temporal causality. It is like saying that suppose an event X happens at a location s and another event Y happens in a location s'.

Then can we say that the a like $X(s)$ caused $Y(s')$. Can we say something like that or like similarly temporal causality like let us say some event happened at time t and another event happened at time t' where $t' \geq t$. In that case can we say that $X(t)$ causes $Y(t')$. So, note that in this case like in case of temporal causality this it is an important constraint is that $t' >= t$.

Because, this much we can say for sure that the a like the cause must precede the effect or at least the effect cannot precede the cause that is a something which we understand well enough. So, in the temporal domain there is there has to be this kind of a natural constraint on which can be a cause and which can be an effect, but in the spatial domain there is of course, no such constraint.

Now like when people try to answer this question they sometimes do it in a lab setting or in a control setting where they actually like change the value of one variable and see if the value of the other variable also changes accordingly.

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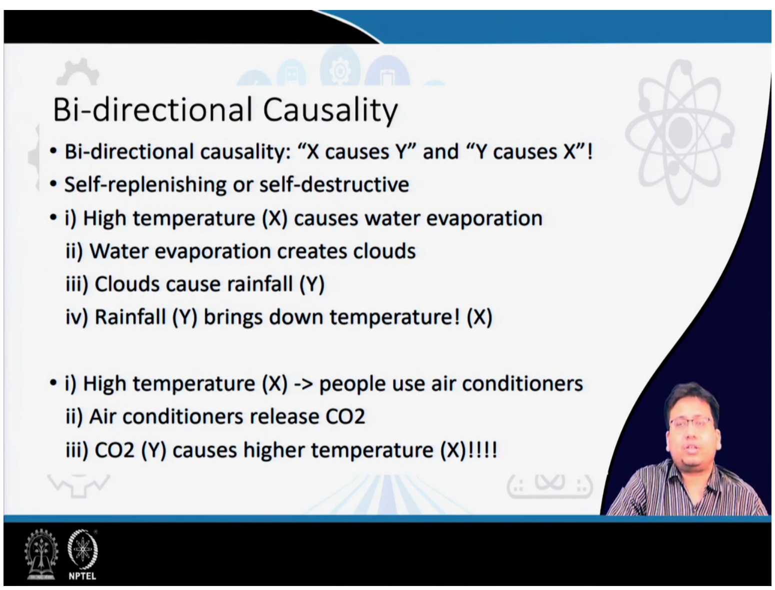

So, like in such a controlled setting we can like where we have control over like at least one of the parameters then we can do this kind of experiment. But, in general or in many settings especially those related to earth sciences we do not have any such luxury that is we cannot really control the value of one particular atmospheric variable or geophysical variable and see it is a impact on other variables that is we cannot automatically make one place hotter and see if that results in a higher rainfall or something like that.

So, that is so we like in the when it comes to the domain of earth sciences we do not have the facility of such controlled experiments. So, we have to depend entirely on the data. Now the causality can be bidirectional also, it might happen that X causes Y and Y causes X are simultaneously true and this can there are like two kinds of processes one k is like one set is or one kind is the self replenishing process the other is the self destructive process.

Say for example, like we know that high temperature causes water evaporation. Now water evaporation causes clouds and clouds cause rainfall and then rainfall brings down the temperature. So, if high temperature is X or if temperature is X and rainfall is Y, then like we can say that like X impacts Y and Y in turn impacts X, but in a different way that is like increase of X should also cause increase of Y and then increase of Y should cause a decrease of X.

So, this is a an example of a self destructive process. Now what I explained just now is actually quite simplistic I mean the it this is not how exactly things happen I mean the relation between temperature and rainfall is not just the like this. There are many other factors also involved, but this is just to give you a simplistic example of a self destructive process as a on the other hand there is self constructive process also sorry I mean self replenishing process also.

Say high temperature means that the people will use air conditioner. But air conditioner causes the release emission of carbon carbon dioxide in the atmosphere and it is well known that higher the emission of carbon dioxide, the higher will the temperatures be. So, this is a case of a self replenishing process which is sometimes also known as a vicious cycle.

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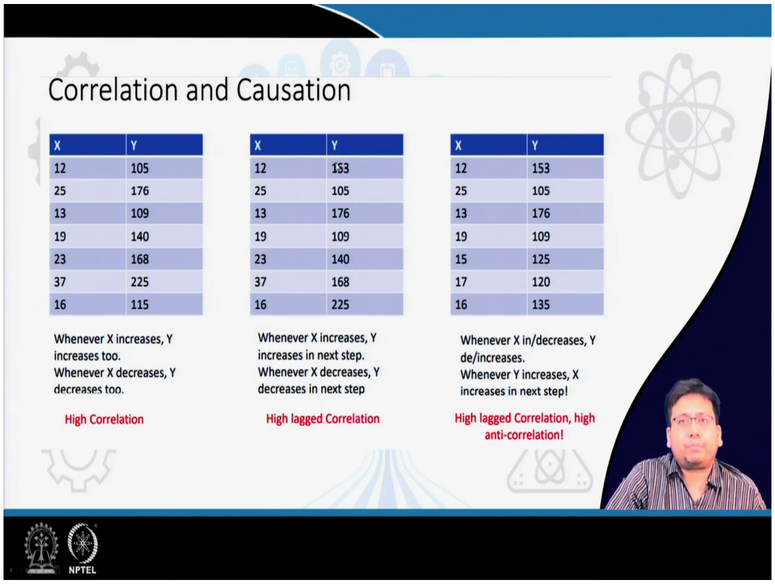

Now, when we have two variables let us say we have observations of both of them, then one like we can like one idea we know or what to do with two variables is to calculate their correlation that is their Pearson correlation coefficient. So, let us say that these are the two observations of two variables X and Y and now here you can see that whenever there is from and let us say that these observations are time indexed that is this is $t1, t2, t3$ etcetera in a like; in a like in the chronological order.

So, here you can see that whenever X increases from $t1$ to $t2$ and then again say from $t3$ to $t4$ etcetera. It like correspondingly there is an increase in Y also. But, whenever there is a decrease in X there is similarly also a decrease in Y. So, like in this case we will see a very high correlation between X and Y, but if you come to this case this is an example of what is called as high lagged correlation. So, here if you see the contemporary relations between X and Y, so here you see X increasing, but Y decreasing.

Here we see X decreasing and Yincreasing. Here X increasing again Y decreasing. Here again X increasing, but this time Y also increasing this time again X increasing Y also increasing and so on and so forth. So, here we do not see any clear correlation between X and Y, but here we can see a lagged correlation it is like saying whenever X increases in one , then in the next step we see Y increases. From $t1$ to $t2$, X increases from $t2$ to $t3$ Y increases from $t2$ to $t3$ X decreases from $t3$ to $t4$ Y decreases and so on.

So, this is an example of high correlation, but lagged in. So, if you like instead of considering $X(t)$ and $Y(t)$ together, if you consider $X(t)$ versus $Y(t - 1)$ then we will be able to get very high correlation coefficient as in this case and then it can also be something like this. So, say if you now if you see in this case we see X increases Y decreases, X decreases Y increases, X increases Y decreases, X decreases Y increases.

So, here it looks like perfect anti correlation whenever X, 1 increases the other decreases. So, in this case we can expect a correlation coefficient close to (-1) while in this case the correlation coefficient would have been (+1), in this case it is like (-1), but, if you consider the lag then again we find that the lagged correlation becomes high closer to 1. So, here like from 12 from $t1$ to $t2$ i find X increasing from $t2$ to $t3$ i find Y increasing $t2$ to $t3$ X decreases $t3$ to $t4$ Y decreases and so on and so forth.

So, these are like so like this is an important concept of correlation like the purpose of this example is to introduce the like the concept of lagged correlation which is often very important in the domain of earth system science, but it, but earth scientist earlier often used to like use this tool of correlation to like infer or imply some kind of causal relation between different variables.

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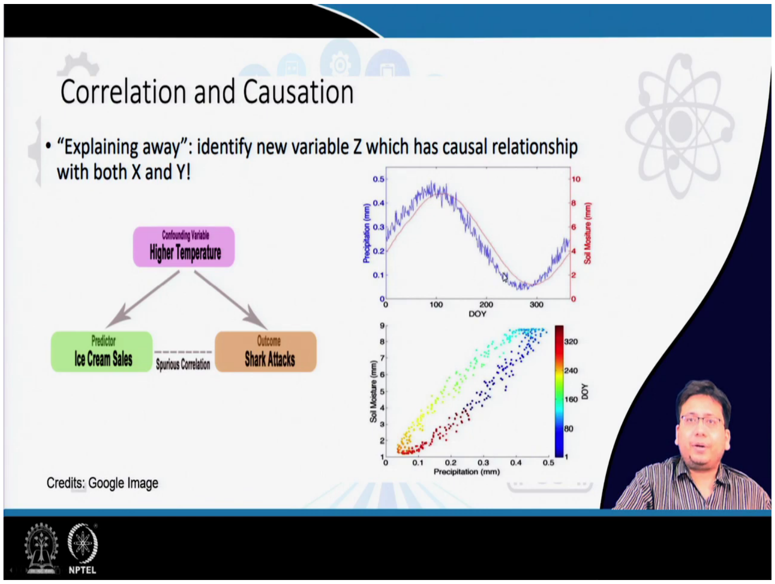

But we, but it is now well established that correlation and causation are often very different things and especially because of the presence of a concept known as a confounder. So, take an example it is a it might be found from data that whenever like ice cream sales increase in a region let us say near a sea beach then shark attacks also increase in that region.

So, does it mean that we can like focus on the ice cream sales or any given day to predict whether shark attacks are going to take place or not sounds quite ridiculous I mean physically there should be no reason why ice cream sale should have anything to do with shark attacks. But, still we do see a very high correlation.

So, why a after deliberating a lot it turns out that there is the presence of a common cause of both of them namely temperature. On those days where temperature is high the people naturally tend to buy more ice creams and however, high temperature also causes the sharks to become restless, it also causes more and more humans to like swim in the sea and hence there is a increased chance of shark attack.

So, the relation between the ice cream sales and shark attacks is actually an indirect one there is a common cause of both of them, this is the higher temperature. So, this kind of phenomena is called as explaining away, that is, higher temperature explains away both of the factors the I mean the both of the so called cause ice cream sale and the so called effect shark attack.

Now we actually neither is the actually the ice cream sales is not the cause of shark attack the cause is the high temperature and ice cream sales and shark attacks are both the effects.

However, if we consider that only the two effects we see a high correlation between them such a high correlation is sometimes called as spurious correlation. I mean the that high correlation has happened because of the dependence on some other common factor.

Similarly in the domain of earth science we are like let us say that in a particular region I like plot the soil moisture as a function of the date of the year and I find so this red curve this follow this is the curve of the soil moisture measured in millimeter on different days of the year starting from 1st January to say the 31st December.

And here you see a more or like this kind of a perfect cyclical pattern periodic pattern something resembling a sine wave or something like that. Now so can we say that like soil moisture is a seasonal quantity, there is some season where the seasonal soil moisture is high and then again it falls off. So, it turns out that in this case the there is this factor this effect can again be explained away by precipitation. So, we know that it is really precipitation which is seasonal and that is and the soil moisture is actually dependent on the precipitation.

So, it is; so it is; so it is a situation like precipitation depends on date of the year because we know that precipitation is a is seasonal quantity and then whenever the precipitation is high then the soil moisture is also high, whenever precipitation falls then soil moisture also falls. So, again like by looking at just the soil moisture data we may be tempted to think that date of the year is the cause and soil moisture is the effect.

But, the fact is date of year is actually the cause of precipitation and precipitation is the cause of soil moisture. Of course, it is like its scientifically incorrect to say that date of year is the cause of precipitation, but in this case date of year is just taken as the proxy of other variables we would like which we would like which periodically or seasonally. So, like so just take that loose statement as of now.

So, like basically this is the concept of confounder that is the by confounder what I mean is the hidden variable. In this case the hidden variable actually like is the common cause of both the things being observed and in this case the hidden variable namely precipitation is something that lies in between the so called cause and the effect ok.

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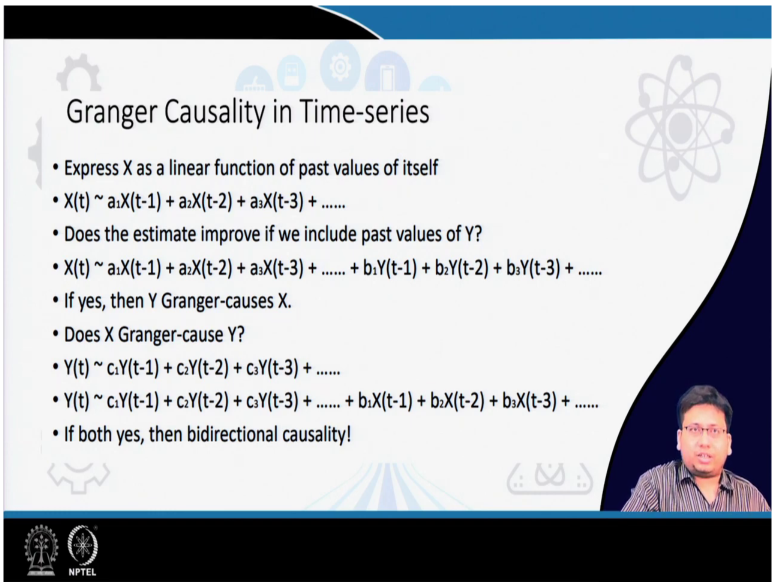

Now, so now how to quantify the causal relations. So, let us say we have a like X and Y we have a time series of two variables and now the question is like can we say that X causes Y or Y causes X or both of them. Now like there are many ways or in which this kind of question they try to answer one or one well known definition of the causality is the Granger causality which is basically based on the concept of regression.

So, if you remember we had earlier studied the concept of auto regression, where we tried to express the current value of a particular variable in terms of the past values of that same variable. So, let us say I try to express X like the variable X as some kind of an auto regressive process. Let us say a third order auto regressive process or any kth order auto regressive process.

So, we write $X(t) \sim a_1X(t-1) + a_2X(t-2) + a_3X(t-3) + \ldots$ and these a_1, a_2, a_3 these are the different coefficients ok. And now like we know we have already discussed how to estimate these coefficients by using ideas like some least square regression or parameter estimation or something like that.

Now, now suppose I try to express X as a an auto regressive process. Now the question is instead of making it an auto regressive process that is instead of trying to express X in terms of its past values will the estimate improve if we bring in the past values of another variable let us say Y. So, that is like while express that is while retaining these predictors can we introduce some more predictors which are the past values of Y and each of them comes with a certain coefficient? If yes then we can say that Y Granger causes X.

Now, what exactly do I mean by yes? I mean so here we are we can try to estimate $X(t)$ like that we will always be able to fit some suitable values of a_1, a_2, a_3 etcetera by least square regression. In this case also since we have the observations we can also estimate these coefficients of Y named the b_1, b_2, b_3 etcetera. So, once we estimate both of these the coefficients of both of these models we can use both models for predicting future values of X.

And now if it turns out that the second model predicts X better than the first model then we can say that basically means that including the past values of Y actually helps us to improve the prediction of X. So, the so in a sense we can say that the past values of Y cause the future values of X. So, we that basically is the idea that is these thing can they can be like written as Y Granger causes X.

Now, if we a want to ask does X Granger cause Y? So, then the same thing the same question we can like the same equations we can write in the reverse way and a its possible that both of these are yes, that is like including Y to predict X improves the prediction of X and including X to predict Y actually may improve the prediction of Y. So, in that case we can have we will have bidirectional causality that is X Granger causes Y and Y also Granger causes X.

Alternatively only one of these may be true or it may it is possible that none of these will be true in which case we will mean which will mean that there is no causal relation between X and Y.

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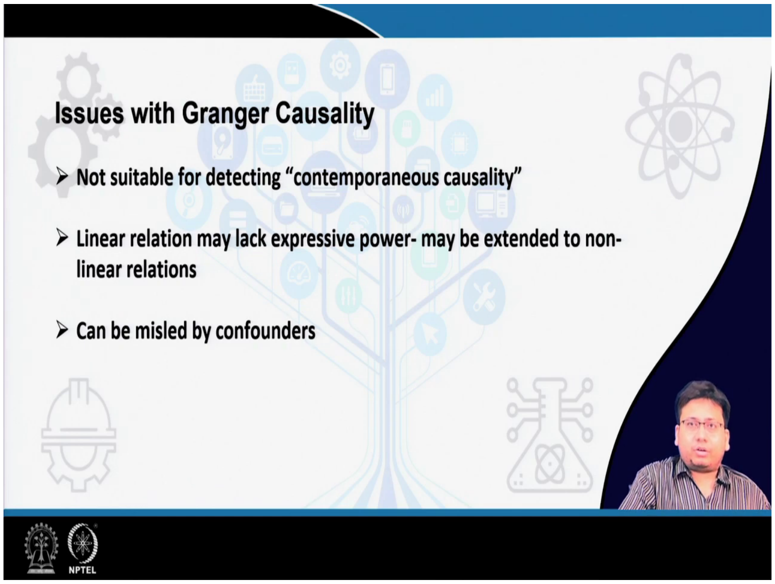

Now, so here this Granger causality this is a relatively straight forward model. One just needs to solve estimate these predictors and like use the models to make to evaluate the future predictions. The, but the there are various issues in this Granger causality approach. First of all it is not suitable for detecting contemporaneous causality. So, note that we are that is, if X like that is if like we can say that Y Granger causes X.

So, basically it means that the past values of Y are being used to predict the future values of or current values of X that is, but we cannot say that like the that is we cannot include $Y(t)$ as a predictor in this case. So, that is like suppose it happens that is if at any given point if Y increases then that has an impact on X also if Y decreases that has an impact of X also I mean at the same time point.

Such things such relations cannot be expressed in this thing the reason is that like of course, I can bring in $Y(t)$ as a predictor of $X(t)$ in this equation, but suppose I get a non-zero coefficient of that then also I mean there is actually the problem is arising because if we have $Y(t)$ here and it has a non-zero coefficient also we still cannot say that whether X is causing Y or Y is causing X.

Because it is like it is in a sense it is a symmetric relation that symmetry is broken by ensuring that here we are considering only the past values of Y. So, like we have we already discussed that the cause like cannot succeed the effect I mean the I mean I the cause can either be contemporaneous or it can precede the effect. So, in this case because the like it $Y(t - 1)$ is happening before $X(t)$, then we can say that if this hold then definitely Y is the cause and X is the effect. X cannot be the cause of Y that is $X(t)$cannot be the cause of $Y(t - 1)$.

But, $X(t)$ can very well be a cause of $Y(t)$. So, it like including $Y(t)$ as the predictor here does not help in the like in the like in our causal analysis. So, this Granger causality is not suitable for detecting contemporaneous causality and next is that like here we are using a linear regression to predict the future value or current values of X, but that may lack expressive power.

So, why not go for a non-linear model. So, that is actually not so much of a problem linear that the basic concept keeping the basic concept of Granger causality intact we can move from the this kind of a linear model to a non-linear model like something like a neural network. In fact, people do that also.

And a bigger problem of Granger causality is that it can be misled by confounders. So, these kinds of confounders we already talked about. Now if we try to do the Granger causality analysis it there is no straight forward way to like eliminate the presence of these confounders that is if we do the Granger causality analysis on a data set like this we may actually end up predicting shark attacks based on ice cream sales like we will not that is there is nothing in the Granger causality framework per se which warns us that this or which indicates that this is happening because of some confounder.

So, of course, like various hacks can be incorporated by bringing in more and more variables and taking pairs of these variables and forcing Granger causality relation and seeing which relation is actually stronger is the ice cream sale to shark attack relation stronger or is the temperature to shark attack relation stronger and things like that, but those you can say they are post processing these things are not part of the Granger causality framework per se.

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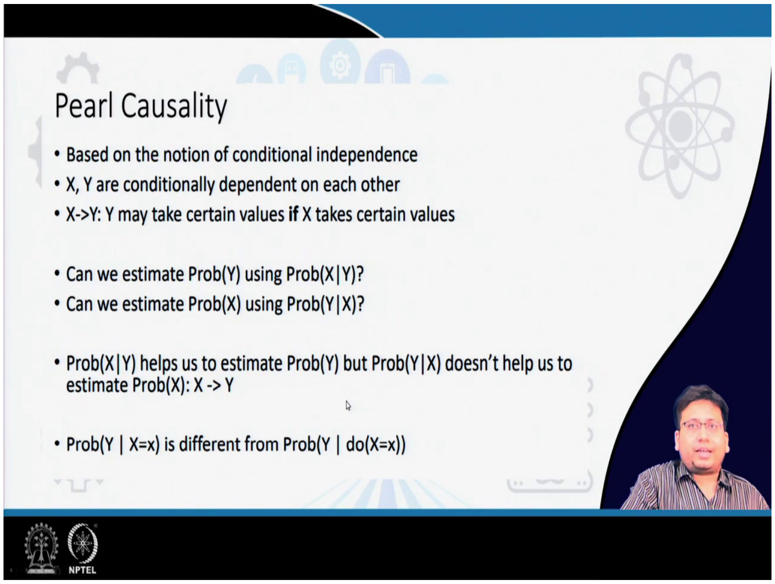

So, the Granger causality framework by itself does not like help us to eliminate the confound or identify the confounders. So, based on that there is an alternative approach of causality which is called as Pearl causality, this one is actually based on the concept of conditional independence. So, like we try to measure things like let us say X and Y are two variables like we try to measure whether they are conditionally dependent on each other by that I mean that like can we say that like can we define some kind of a conditional probability distribution like this.

And then in this kind of conditional probability distribution we can actually add various other variables that is potential confounders we can add to these conditions and see whether these conditional distributions change or not in the presence of the other variables. So, if so like a like if they are found to change then we then it might suggest that that variable is let us say it is a confounder or may be in some it is not a confounder or something like that and so on.

So, basically this pearl causality framework it allows us to like this like unlike the Granger causality which is based on regression this Pearl causality is based on the notion of conditional independence.

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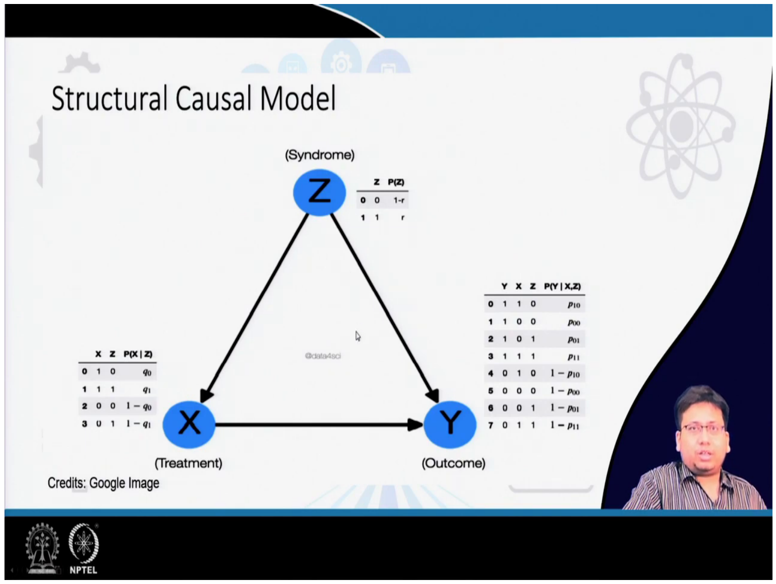

And similarly there is another idea known as the structural causal models where we actually try to like estimate the like actually try to form something like a graph between the different variables and a for every graph we try to define some kind of a probability distribution of possible values of that variable based on the values of other variables in that graph.

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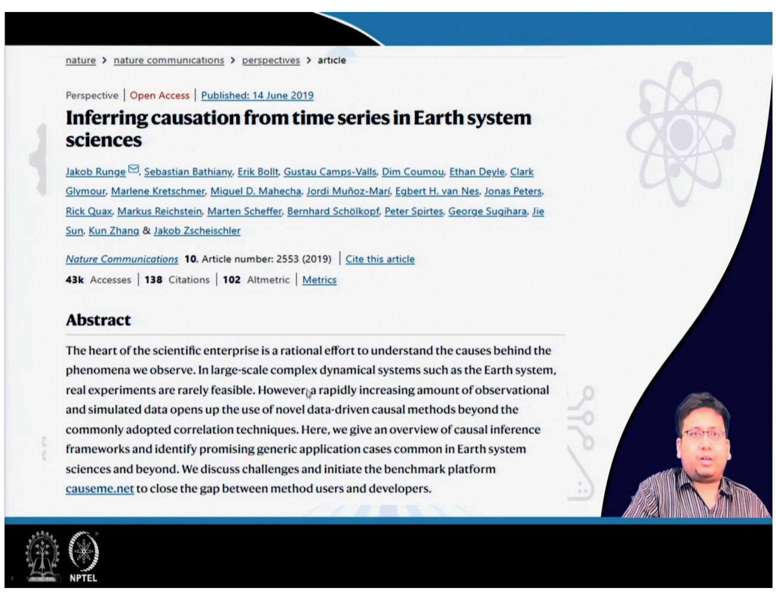

So, like so this is an example of a causal graphical model. So, we will come back to it at some stage. Now this topic of inferring causation from time series like this is like increasingly important in the domain of earth like earth system science where like climate scientists have been focusing in recent times to like use the vast volumes of data to identify these kinds of causal relations.

So this paper appeared in nature communications in 2019. The first author Jakob Runge he is like he is leading expert on the on this topic of causality especially the notion of pearl causality based on extreme on this conditional inference.

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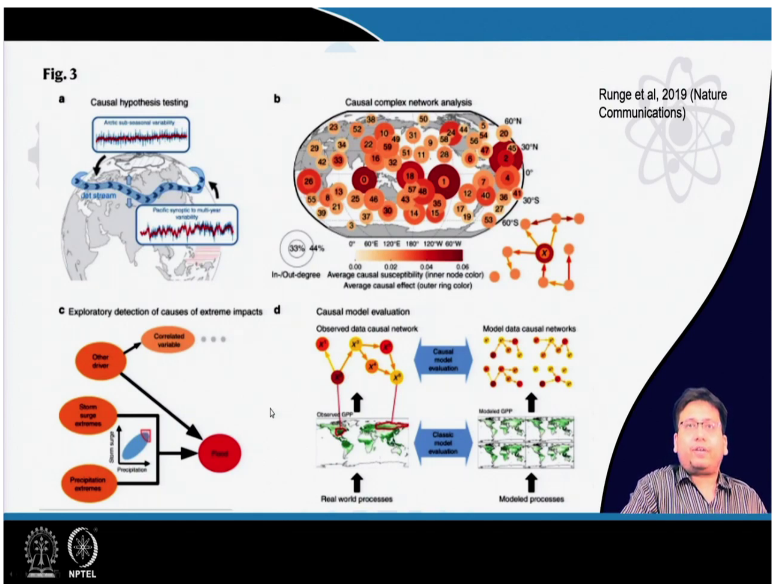

So, this like these are images taken from this paper, it shows us some various applications of the concept of causal of this causality in various problems related to earth science. We will visit this in more detail at a later stage. So, we like for example, let us say we have a hypothesis that one particular climatic phenomena impacts another is the cause of another climatic phenomena.

So, like so that is something like a causal hypothesis. Now can we use statistical techniques to do the to test this hypothesis or then like a more ambitious aim is to build something like a complex network or a causal complex network where we actually like a identify or like we try to build a network of causes and effects of various climatic phenomena all over the world, then another thing is like various extreme events we have already talked about in detail in the past two lectures.

So, suppose an extreme event happens can we attribute some particular cause to it? Can we say that this heavy rainfall here happened due to some low pressure system elsewhere or can we attribute a particular event like say a devastating drought or something like that, can we attribute it to the global climate change or that is to say can we say that had climate not changed or had climate changed not happened then this kind of a drought would not have happened.

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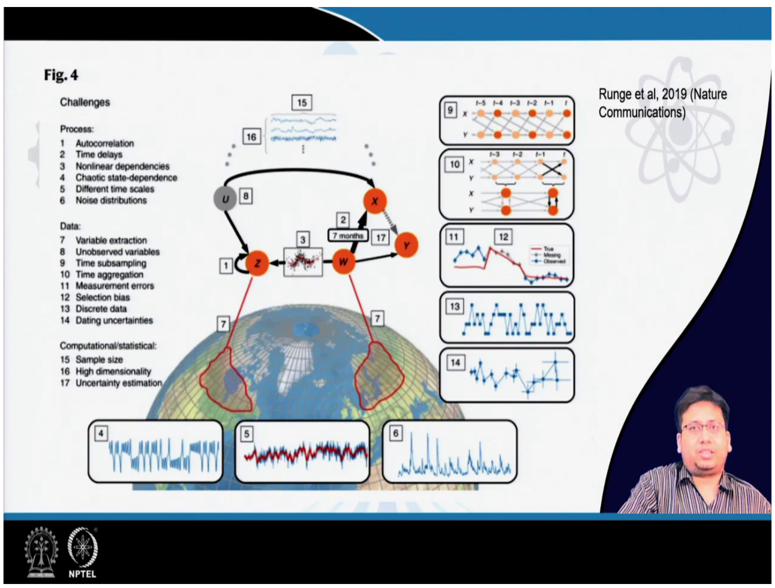

So, these are actually questions related to counter factual scenarios I mean climate change we know is happening, but whether individual events can be attributed to climate change or not that is a much more difficult question. I mean to answer that question we have to consider an alternative scenario known as the counter factual scenario where we are and there we have to see whether in such a scenario whether this would have happened or not, but such a counter factual scenario the problem is that the counter factual scenario has not happened.

So, how do you know whether it would happen or not? So, for that purpose people develop climate models and like where they can actually run the simulation or they can simulate the climate in under various hypothetical settings. But, then developing these models itself is a complicated like is a very non-trivial task where we have to preserve the causal relations that are already known they have to be preserved perfectly in those models and that itself is a difficult task.

So, like when we the various there are various challenges associated with applying the concepts of causality in earth system sciences. So, these include the challenges include these autocorrelation. Autocorrelation hampers the estimation of causality, then lags we already talked about the this issue of lags. So, it is possible that like if you remember that table involving different lags. So, unless we identify the particular lag value we may not be able to understand the or quantify the impact of the causality so well.

So, there are more factors like this at a later lecture we will try to understand all these issues and how they these issues are I mean how these are these challenges arise in the domain of climate science and how we or especially or earth system science in general and how we can possibly solve them.

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So, these are a couple of references in which these concepts of causality has and their possible applications in the domain of earth system science has been discussed, especially the first paper although we will discuss this paper in detail at a later lecture. So, but for a like for some initial studies or to get an initial idea of how causality can be applied in earth sciences I recommend you to go through this paper.

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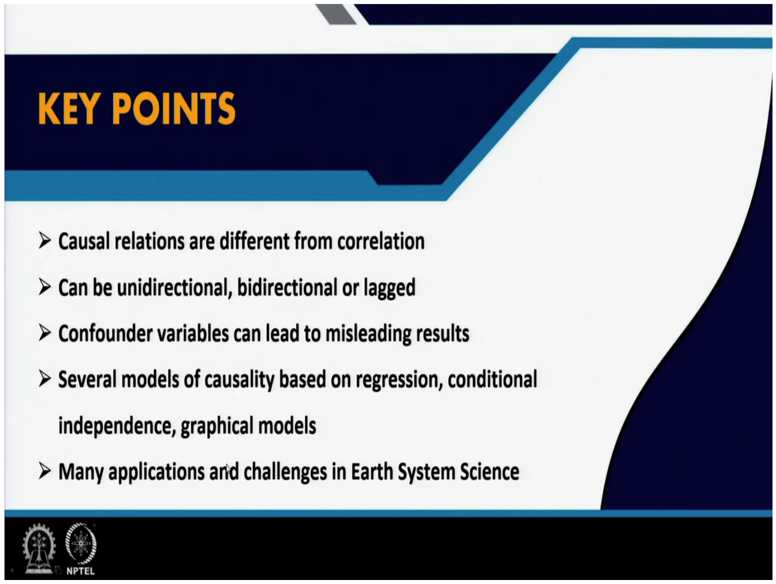

So, the key points to be taken from this lecture are as follows: The causal relations are different from correlations; the causal relations can be unidirectional bidirectional or lagged; the presence of the confounded variables can lead to misleading results. There are several models of causality based on regression, conditional independence, graphical models and so on.

And then there are many applications in earth system sciences, but they also come with various challenges ok. So, that brings us to the end of this lecture. In the subsequent lecture we will like focus on a few more topics and this topic of causality we will come like we will come back to it maybe sometime in module 3.

So, till then bye.