Natural Resources Management (NRM)
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Week – 06
Lecture - 35
Modeling and Simulations Applications in Agriculture for NRM
Part 3

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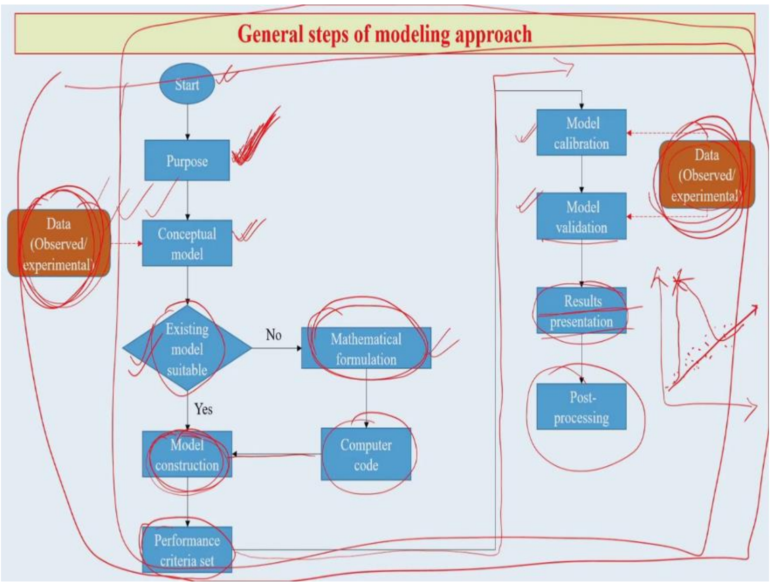

So, continuing modeling and simulation applications, in a previous lecture, we discussed about various general steps of modeling approaches. Now, we will go into different aspects of these models one by one.

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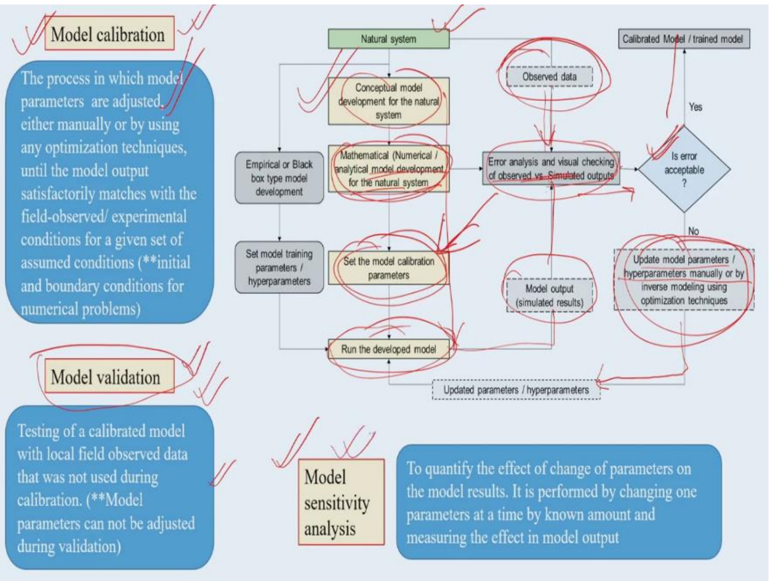

So, model calibration. As I said that model calibration is one of the most important part of modeling exercise. If our calibration is not correct, then the modeling exercise will be totally unsuccessful. What we do in calibration, actually? In calibration, we basically try to adjust various parameters and we try to do it manually or by using any kind of optimization technique until the model output becomes satisfactory; satisfactory for our purposes and it does match with the field observed or experimental conditions for a given set of conditions.

So, I repeat again in model calibration, what we try to do is to adjust various parameters in the model manually or through different optimization techniques, till the point that we get the outcome from the model which are satisfactory and which are also in sync with the field or observed values or observed results. Once it matches, then we can say that our model is calibrated and it is ready for further function.

Now, the model you will try to then validate. Validate is a testing of a calibrated model with local field observed data which you have not used while calibrating this model. So, remember, while you calibrate the model, you also use field data, but while you validate it, you use also field data, but that should be different set of data than the one that you have used for model calibration.

So, in case of validation, if you find that using this calibrated model, you are able to get the outcomes which are almost same with the field observed value, means that in another different field, observed value, then you can say that yes your model is calibrated and it can now give me results for different fields. Once this is ready, then you start your actual experiment, actual analysis with the model.

Now, for any natural systems, as I said in the previous lecture, that conceptual model development for any natural system is a critical step. Now, once your conceptual model is ready, you are clear in mind then you go for mathematical, numerical, analytical or whatever type of model that you want for a particular natural system. Now, to run these kinds of model, of course, from that natural system, you need in your hand good amount of observed data.

Now, here when you choose any kind of model, then you also look at the observed data and you check those observed data, whether these observed data are of good quality, whether there is any errors or so. So, from the mathematical or numerical analytical model development of particular natural system, you actually try to check the quality of the data any error whether it is there.

Now, if there are errors, then you go for different process, which I will come in a minute. But if you are happy with your data set, then then you start doing you are setting the model calibration parameters. So, once your model calibration is done, then you go for validation and then you run the developed model.

Parallelly what is happening here, when you are conceptualizing the model, you can actually as I said in previous lecture, you can try to think of using certain existing model as well; empirical or black box type of model or any other model. So, on the other side, if your observed data you find there are some errors, then you need to see whether this error is still, acceptable if they are acceptable then you go for of course, calibration means this step, if they are acceptable, you go ahead with calibration. But if the errors are not acceptable and certain parameters which are very critical and you feel that little bit of error can also affect your model in that case, what you have to do, you have to now then update your model parameters and that is a very cumbersome exercise.

Here you have to process your model parameters manually or through inverse modeling using various optimization technique. So, that exercise might take some time, but you cannot avoid if your judgment says that the error for the particular parameter observation is not acceptable. Instead of going doing entire exercise, it is better that you check here rectified through various processes and then this information or data you can feed in into the model and then again run with the revised or relatively error, minimized error or error free data sets.

Then you run once you run then you get the model output or the simulated results. That simulated output again you check here whether they are okay, whether the results which are coming is meaningful satisfactory to your expectation or purposes. If it is satisfactory, then the modeling exercise end there, then comes representation of your result of modeling exercise, which is another very important part of this simulation modeling study.

Now, one part that I have not discussed till now, which is critically important for a good model development or model run is model sensitivity analysis. To quantify the effect of change of a particular parameter. Suppose, you are running a model where rainfall is an input parameter and you find that any slight change of rainfall, amount of rainfall, it changes significantly your model outcome or output.

So, that means, you can say that your model is very sensitive to rainfall data or rainfall input parameter. So, to quantify this effect of change of a parameter on the model results we carry out model sensitivity analysis and it is performed by changing one parameter at a time by a known amount and then measuring the effect in the model output.

Now, I give an example of suppose a crop model where you want to see the impact of rainfall, whether it is sensitive for your model outcome or not. So, what we can do is that we can change the value of the rainfall suppose fifty-millimeter rainfall what is the outcome, sixty millimeter what is the outcome, hundred millimeter of rainfall what is the outcome and if you see that there is a significant changes in the outcome, we are sure that our model is very very sensitive to rainfall.

As far as the outcome model outcome, which is your crop yield. So, that means crop yield is very sensitive in your model towards rainfall input parameter. So, that is why it is very critical that these three exercises model calibration, model validation and model sensitivity analysis are carried out with great sincerity.

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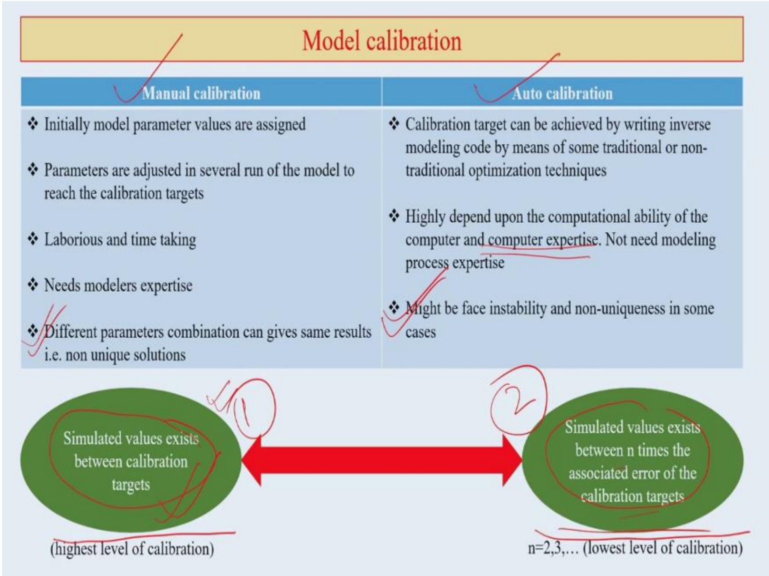

Now, we will talk about one by one these three very important functionality or processes in modeling exercise. Model calibration, we discussed that why we do it now, model calibration can be done in two-way, manual calibration and auto calibration. In case of manual calibration, initially model parameter values are already assigned. Parameters are adjusted in several run of the model to reach the calibration target that you have fixed, and this calibration process can be very much time taking and very laborious too. Lot of time actually people spend while calibrating their model.

As I said that if your calibration is not good, then certainly the model outcome will not be of that quality. So, needs little bit of experience and expertise to carry out this calibration exercise in case of modeling and simulation. Different parameter combination can give same result that is non unique solution. So, suppose rainfall, humidity, temperature, wind, wind speed, together the combination of these parameters can give you same result.

Now, if you go for suppose auto calibration, in some model you may have that option. Calibration target can be achieved by writing inverse modeling code. What is that? That is by means of some traditional or nontraditional optimization technique you may follow for auto calibration.

It highly depends upon the computational ability of the computer and also the person who is running the calibration. He or she must have certain amount of expertise about computer, running computer, and also how actually computer behaves, he or she must know about that. But even if she does not have any previous modeling expertise still in case of auto calibration, he can carry out the task.

Sometime a person or individual may face a little bit of instability or non-uniqueness in some of the cases while carrying out the auto calibration. So, that, you have to somehow address these issues by multiple times of auto calibration exercise. Now, as you see that simulated values exists between the calibration target, this is one condition. Simulated values exist between n times the associated error of the calibration target, these two conditions you can get.

So, this one we call as the highest level of calibration and the right-hand side where simulated values exists between n times the associated error of the calibration targets, we call that as the lowest level of calibration. So, to these two kinds of situation that you might face while calibrating your model.

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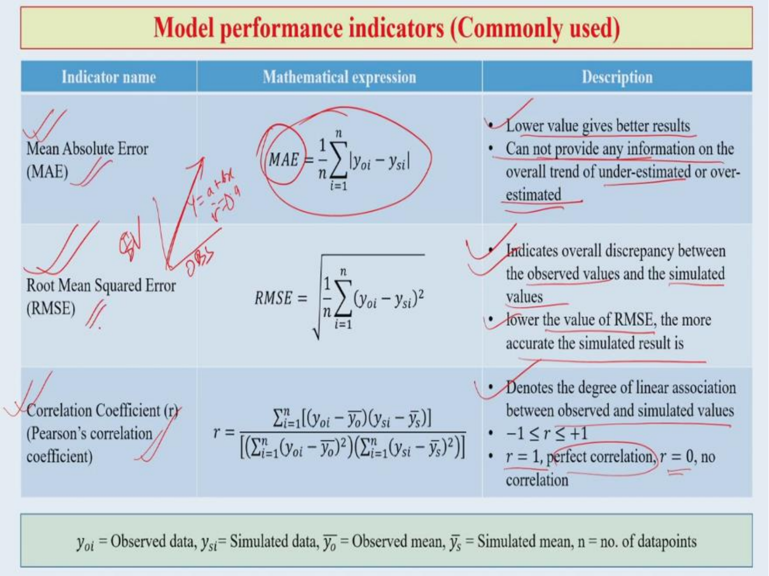

We must know about the performance of our various indicators in our model, because each indicator could actually impact the model process and thus the model outcome, I will discuss a few of them. One indicator could be mean absolute error (MAE), so, you calculate MAE in this manner.

Mean Absolute Error (MAE) is equal to the average of the absolute differences between the yoi (observed data) and ysi (Simulated data)

yoi is observed data, ysi is simulated data, n is the number of data points

So, lower values of MAE give you better result and it cannot provide any information on the overall trend of underestimated or overestimated values.

So, if your MAE value is less, it is better for you, because then your model result will be better, but we also should remember that it cannot provide any information on the overall trend of underestimation or over estimation, because in modeling exercise, we often face this kind of problem of under or over estimation.

So by different, run different run and some adjustment of input parameter, you can actually come, you can reduce these overestimate or underestimation that is that is you learn with different, multiple running of a particular model.

Root mean squared error (RMSE) very, very popular and known indicator for modeling performance testing. Here, RMSE indicates your overall discrepancy between the observed values and the simulated values most of us actually will see that we do go for RMSE to test in our performance of our model. Lower the value of RMSE the more accurate the simulated result is.

Now, third correlation coefficient most popular among all of us. Pearson correlation coefficient is also an indicator for testing the model. Often we see a kind of a straight line, if your data is like that, then you come with some straight line and then you come with r value if r value is, quite high then you say that, this is a fantastic correlation between different variables or parameters. So, correlation coefficient, what it does? It denotes the degree of linear association between your observed and simulated values, your observed and simulated values. So, higher the r value better is your result.

So, denotes degree of linear association between observed and simulated values and r is equal to one is a perfect correlation r is equal to zero is no correlation. So, ideally we try to test and try to find out the different values of these different indicators. In some cases we are happy when the value is high, in some cases we are happy when the value is low depending on the nature of indicator that you are going to use.

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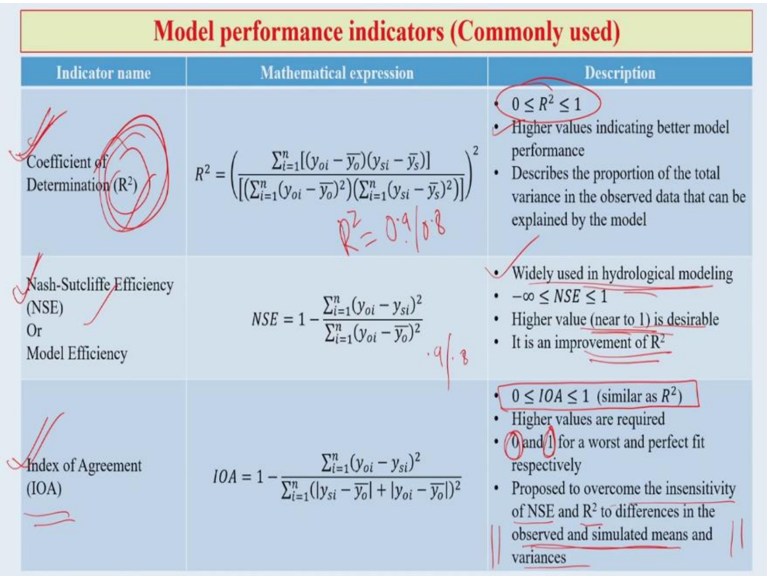

Next indicator coefficient of determination (R-square). Now, R-square values lie between one and zero we know that in case of R-square value higher values indicates better model performance you remember we get very happy if we get R square value zero point nine or zero point eight something like that. So, higher the R-square value indicating better model performance and this R-square value it describes the proportion of the total variance in the observed data, proportion of the total variance in the observed data that can be explained by this R-square for a particular model.

So, next is our NSE or Nash Sutcliffe Efficiency. What it does? This is widely used in case of hydrological modeling higher value which is means near to 1 is desirable and NSE is one step further improvement of R-square, but R-square is still very much efficient, accepted among the modeling community. NSE is just one step, above one step what you call improvement of R square. So, this can be used largely for hydrological modeling.

IOA another indicator which we try to test our performance of our model. IOA, Index of Agreement the values lies between zero and one which is similar like R squared. So, higher values are better indicate better performance by your model zero and one for worst and perfect fit for a model.

So, if it is zero, your model is really bad performing and if it is one, it is absolutely perfect. In fact, when it is one, then also we actually try to figure out that if everything is okay, because one is means it is absolutely fine. So, little less than one like, zero point nine, zero point eight is quite good basically. So, one is perfect situation, another is perfectly bad situation.

So, IOA also proposes to overcome the insensitivity of NSE and R-square to what, to the difference in the observed and simulated the means and variance very, very important, please note this particular point. So, IOA, it helps to overcome the insensitivity of NSE and R square towards the observed and simulated means and variances. So, if that is also taken care of through IOA then actually your performance testing of model become much more robust.

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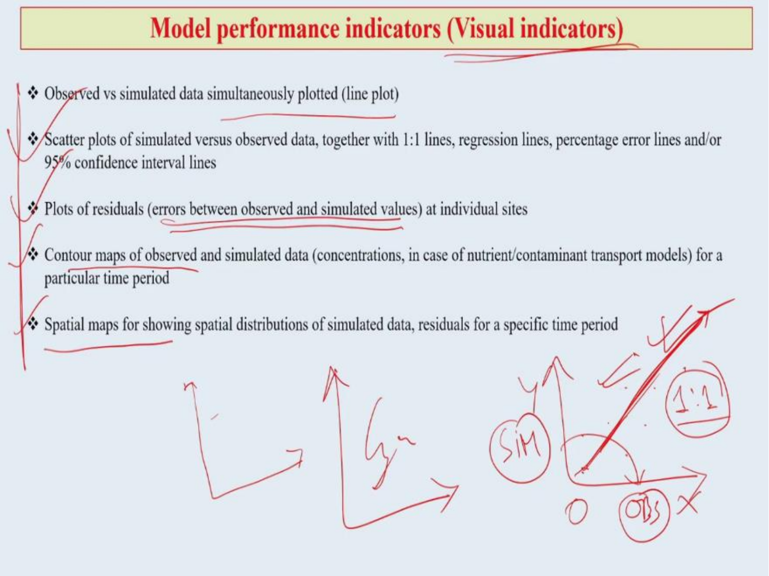

Now, with continuation of model performance indicators like visual indicators, we can always, you know that we try for this kind of graph to see that observed values versus simulated values, if it lies like this this this this this way, then if we get a perfect straight line, and then we say that, simulated values are perfectly matching with observed value and the performance of your model is very good. Sometime people call it as one is to one line for testing the performance of your model.

Now, observed versus simulated data simultaneously plotted in this kind of line plot that I have just mentioned. Then you can have also scatter plots of simulated versus observed data together with one is to one line, regression line, percentage error line or say ninety five percent confidence, interval lines also.

Then, you can have also plots of residuals. These I am talking about all visual indicators, which you can see basically, in graphical form. So, plots of residuals at individual sites that means, errors between observed and your simulated values that also can help you giving some kind of visual indication of your model performance. Contour maps of observed and simulated data also often try to find out the model performances for a particular time period.

Sometime spatial maps also are being carried out for showing spatial distributions of simulated data, residuals for a specific time period. So these all are basically one or other way of visualizing, your model performance through some indicators.