Geo 873 – 001: Seminar in Human-Environment Geography

12:40 am – 3:30 pm; Geo 120

Zoom Link will be added to facilitate renewed needs, staring on Feb. 22, 2023

1) Data mining, in-class exercise of accessing data from WB, FAO, etc.)
2) Introduction of Structural Equation Modeling (SEM)
   - SEM basics(3/1)(Petri Nokelainen, University of Tampere, Finland; petri.nokelainen@uta.fi)

     (https://www.researchgate.net/profile/Salam_Hmood/post/structural_equation_modeling/attachment/59d6551c79197b80779ac68a/AS%3A524275057479680%401502008322465/download/sem_en.ppt)
   - Demonstration by Venkatesh on 3/15
   - Case studies (3/15)

Reading

Venkatesh, K., John, R., Chen, J., Jarchow, M., Amirkhiz, R. G., Giannico, V., ... & Yuan, J. (2022). Untangling the impacts of socioeconomic and climatic changes on vegetation greenness and productivity in Kazakhstan. *Environmental Research Letters*, 17(9), 095007. (demonstrating on March 15 with R Studio)

We used public data sources during 1992-2016 to calculate SES_{m1} and to make cross-entity comparisons between SES_{m1} and other metrics in natural and social sciences.

Chen et al. 2022. ERL

SI-1. Variable names and data sources for SES_{m1} calculations and verifications. GDP in 2020 USD is deflated to constant 2011 dollars using the consumer price index (CPI) from the Bureau of Labors Statistics. Daily carbon price is available. We used the average carbon price of 9.966 Euro per ton of CO_2 and currency exchange rate of $0.7875 per Euro during 2009-2020 due to a lack of price data before 26 October 2009. Livestock was converted to animal unit (Au) equivalents following conversion from livestock to sheep by the FAO (http://www.fao.org/3/y4176e/y4176e04.htm)

Variable (unit)	Source	Webpage
Political Entity (PE) level (1992–2016)		
NPP (g m^{-2} yr^{-1})	AVHHR	http://glcf.umd.edu/data/glopem/
NPP (g m^{-2} yr^{-1})		https://earthdata.nasa.gov/
PET (mm)	CRU@UEA	http://www.cru.uea.ac.uk/data
GDP ($)	SNA of UN	https://unstats.un.org/unsd/snaama/Basic
POP (pers)	UN	https://population.un.org/wpp/Download/Standard
PDSI (-10, 10)	CRU@UEA	http://www.cru.uea.ac.uk/data
LSK (Au km^{-2})	FAOSTAT	http://www.fao.org/faostat/en/#data/QA
HDI (0-1)	WB	https://datacatalog.worldbank.org/
SDI (0-1)	SDI Team	https://www.sustainabledevelopmentindex.org/
LEI (yr)	WB	https://datacatalog.worldbank.org/
CO_2 & N_2O emission	WB	https://datacatalog.worldbank.org/
Prefecture level (2016)		
NPP (g m^{-2} yr^{-1})	MOD17A3	https://earthdata.nasa.gov/
ET (mm)	MOD16A3	https://earthdata.nasa.gov/
GDP ($)	Yearbooks	https://unstats.un.org/unsd/snaama/Basic
POP (n)	Yearbooks	http://data.stats.gov.cn/easyquery.htm?cn=E0103
LSK (Au)	Yearbooks	http://data.stats.gov.cn/easyquery.htm?cn=E0103
Others		
Temperature (^oC)	CRU4.04	https://crudata.uea.ac.uk/cru/data/hrg/
Precipitation (mm)	CRU4.40	https://crudata.uea.ac.uk/cru/data/hrg/
Carbon Price ($ Ton CO_2)	Markets Insider	https://markets.businessinsider.com/

What Is Data Mining?

Data mining is most commonly defined as the process of using computers and automation to search large sets of data for patterns and trends, turning those findings into business (research) insights and predictions. Data mining goes beyond the search process, as it uses data to evaluate future probabilities and develop actionable analyses. (https://bootcamp.rutgers.edu/about/)

In-class exercise

- Find several time series of key variables of SES and examine the inter-dependent changes and relationships between (among) them.
- Explore through simple correlation analysis, or graphic scatter plot
- Calculate cross-disciplinary metrics (e.g., HANPP)

WebPapges:

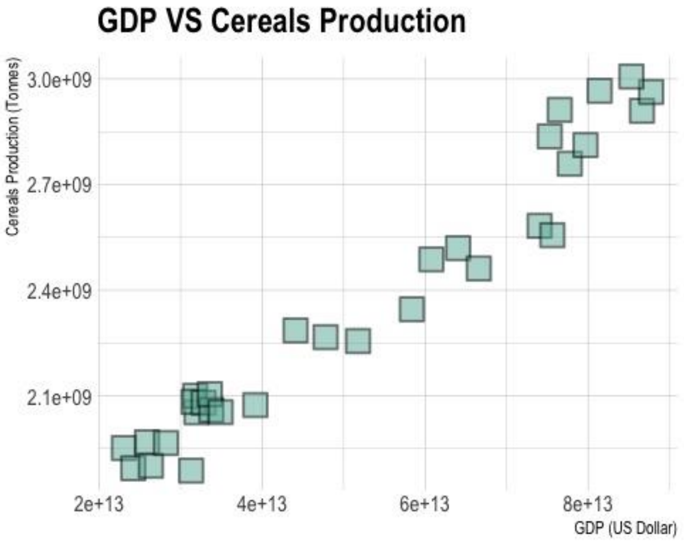
- fao.org
- https://climateknowledgeportal.worldbank.org/watershed/92/climate-data-historical
- http://www.cawater-info.net/index_e.htm
- https://worldpopulationreview.com/state-rankings/most-golf-courses-by-state
- https://www.bea.gov/data/gdp/gdp-state
- https://sidra.ibge.gov.br/tabela/3939
- https://unstats.un.org/unsd/snaama/Basic

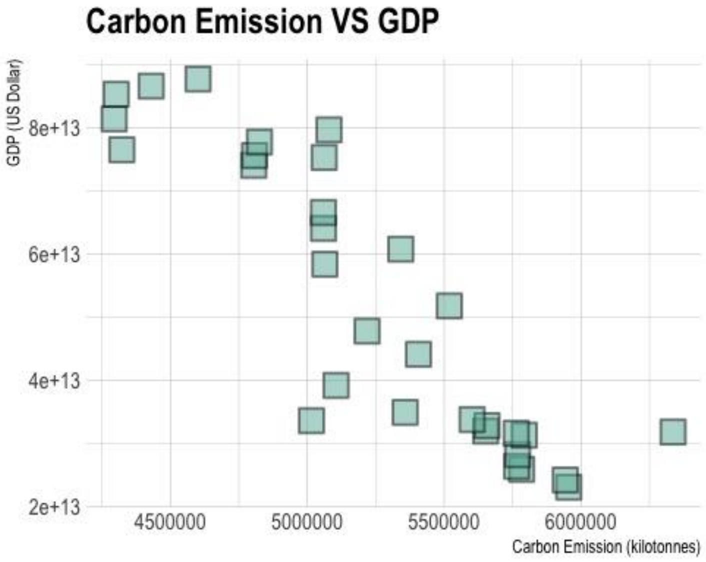
Challenges in data mining:

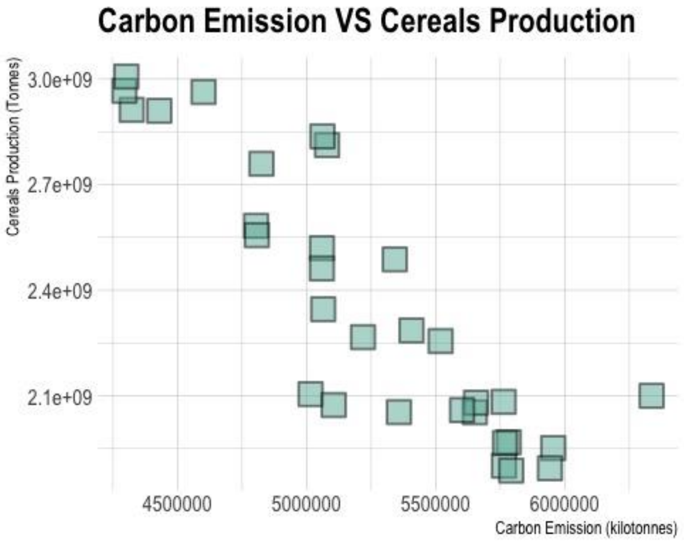
- FAO provides national data, but need subnational information, also need subnational information that is comparable across countries in the same watershed/region
- Not all data sources are current, ex. cawater had data ranging from 1980-1995
- Some sources charge/have a cost associated with using/downloading data
- Unit (e.g., per square mile)
- properly formatting the data [proper row and columns and titles] so that it can be compared/combined with data from other sources while retaining its identity, identifying the methodology of the original data collection (still working on that, may need to email data source owners - common problem with huge data repositories such as the IBGE), and determining at which level to download/parse the data (national, state, municipality, county, city, etc.). Additionally, this amount of data takes a lot of storage/space and thus I couldn't download it directly from the site but had to have it emailed to me from the site.
- Data mutation

Preliminary results:

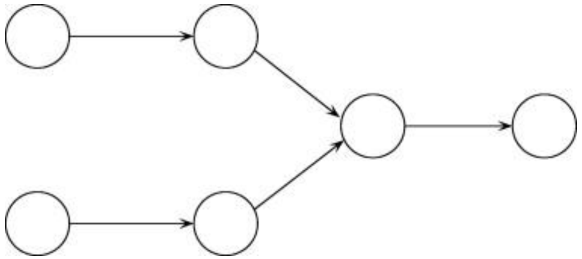
- There may be a correlation between GDP per state, GDP per capita, and the number of Golf courses
- Look population up by age and sex to correlate that data and validate our hypothesis that Golf course have a higher prevenance where GDP/ state and Capita are higher and in states where older populations live. Another data set we could look at is location of the golf courses within the state.
- (1) significant **negative** at 5% significance level between carbon emission on agri. land and GDP; (2) significant **positive** at 5% significance level between cereals production and GDP; (3) significant **negative** at 5% significance level between carbon emission on agri. land and cereals production;







A Brief History of Structural Equation Modeling (SEM) (https://educationalresearchtechniques.com/2016/10/28/a-history-of-structural-equation-modeling/)



SEM is a complex form of multiple regression that is commonly used in social science research. SEM is an amalgamation of factor analysis and path analysis.

1) Spearman was trying to trace the various dimensions of intelligence back to a single factor. In the 1930s, Thurstone developed multi-factor analysis
2) Wright (1920's-1930's) was developing path analysis. Path analysis relies on manifest variables with the ability to model indirect relationships among variables.
3) Jöreskog (1970s) combined the measurement powers of factor analysis with the regression modeling power of path analysis. The factor analysis capabilities of SEM allow it to assess the accuracy of the measurement of the model. The path analysis capabilities of SEM allow it to model direct and indirect relationships among latent variables.
4) First software: LISREL; followed by AMOS (graphic design), R (Lavaan), Python

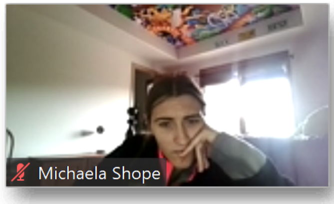
SEM using AMOS

Benefits Of SEM

Here are some of the significant benefits of using Structural Equation Modelling as a technique:

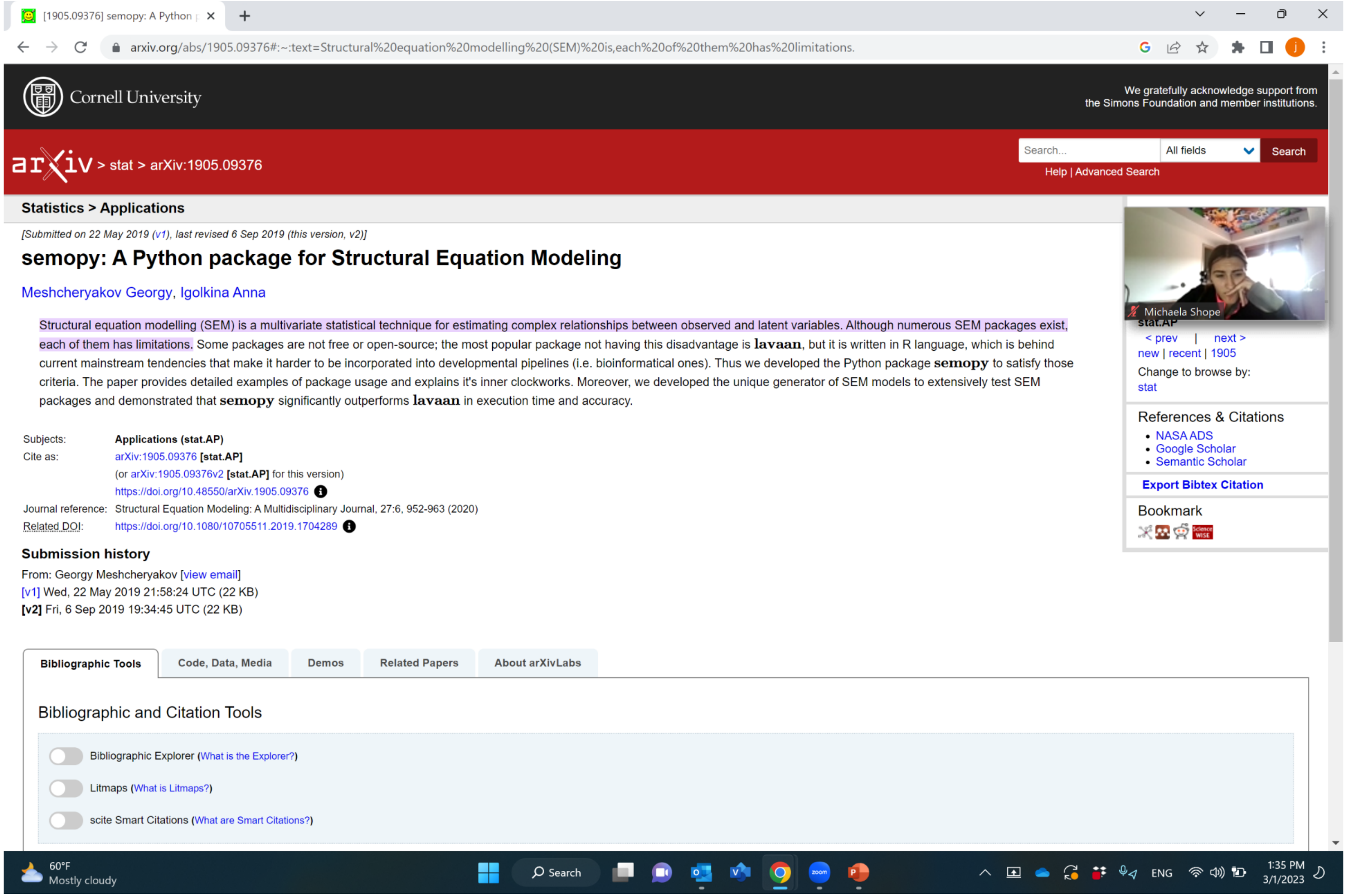
· If you are a researcher looking to expand your scope, using **SEM** would be the ideal choice for the assumptions which brings a lot of clarity and they are testable too.

· It enables survey sampling analyses.



A Brief History of Structural Equation Modeling (SEM)

(https://educationalresearchtechniques.com/2016/10/28/a-history-of-structural-equation-modeling/)



[1905.09376] semopy: A Python p

arxiv.org/abs/1905.09376#:~:text=Structural%20equation%20modelling%20(SEM)%20is,each%20of%20them%20has%20limitations.

Cornell University

We gratefully acknowledge support from the Simons Foundation and member institutions.

arXiv > stat > arXiv:1905.09376

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[Submitted on 22 May 2019 (v1), last revised 6 Sep 2019 (this version, v2)]

semopy: A Python package for Structural Equation Modeling

Meshcheryakov Georgy, Igolkina Anna

Structural equation modelling (SEM) is a multivariate statistical technique for estimating complex relationships between observed and latent variables. Although numerous SEM packages exist, each of them has limitations. Some packages are not free or open-source; the most popular package not having this disadvantage is **lavaan**, but it is written in R language, which is behind current mainstream tendencies that make it harder to be incorporated into developmental pipelines (i.e. bioinformatical ones). Thus we developed the Python package **semopy** to satisfy those criteria. The paper provides detailed examples of package usage and explains it's inner clockworks. Moreover, we developed the unique generator of SEM models to extensively test SEM packages and demonstrated that **semopy** significantly outperforms **lavaan** in execution time and accuracy.

Subjects:	**Applications (stat.AP)**
Cite as:	arXiv:1905.09376 **[stat.AP]**
	(or arXiv:1905.09376v2 **[stat.AP]** for this version)
	https://doi.org/10.48550/arXiv.1905.09376
Journal reference:	Structural Equation Modeling: A Multidisciplinary Journal, 27:6, 952-963 (2020)
Related DOI:	https://doi.org/10.1080/10705511.2019.1704289

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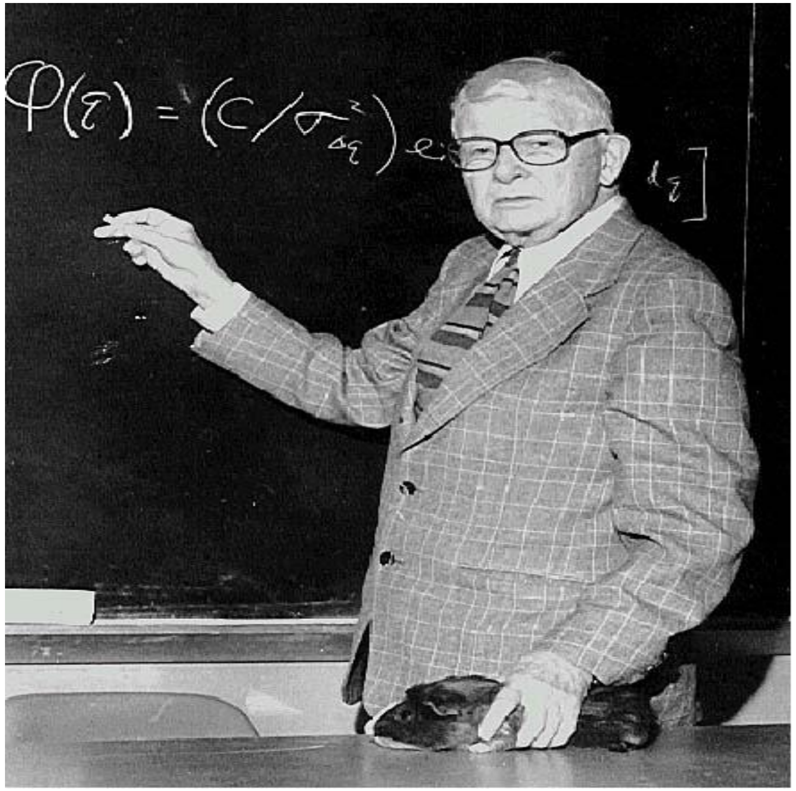
The Origin of Structural Equation Modeling



Sewell Wright (1897-1988)
1st paper in: 1920

The LISREL Synthesis

Karl Jöreskog (1934 – present)
Key Synthesis paper- 1973

Recommended reading (case studies for March 15, 2023)

Chen J, John R, Shao C, Fan Y, Zhang Y, Amarjargal A, Brown DG, Qi J, Han J, Lafortezza R, Dong G (2015). Policy shifts influence the functional changes of the CNH systems on the Mongolian plateau. *Environmental Research Letters* 10(8):085003

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Grace JB (2006) Structural Equation Modeling and Natural Systems. Cambridge University Press, New York

Grace JB, Anderson TM, Olff H, Scheiner SM (2010) On the specification of structural equation models for ecological systems. *Ecological Monograph* 80(1):67–87

Park, H., Fan, P., John, R., & Chen, J. (2017). Urbanization on the Mongolian Plateau after economic reform: Changes and causes. *Applied Geography*, *86*, 118-127.

Tarka, P. (2018). An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Quality & Quantity*, *52*, 313-354.

Tian, L., Chen, J., & Yu, S. X. (2014). Coupled dynamics of urban landscape pattern and socioeconomic drivers in Shenzhen, China. *Landscape ecology*, *29*, 715-727.

Venkatesh, K., John, R., Chen, J., Jarchow, M., Amirkhiz, R. G., Giannico, V., ... & Yuan, J. (2022). Untangling the impacts of socioeconomic and climatic changes on vegetation greenness and productivity in Kazakhstan. *Environmental Research Letters*, 17(9), 095007.

Structural Equation Modeling

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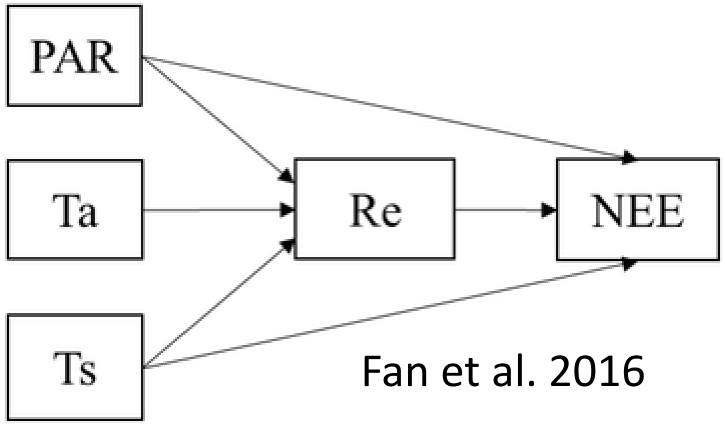
Introduction

- Structural equation modeling (SEM), as a concept, is a combination of statistical techniques: exploratory factor analysis and multiple regression.
- The purpose of SEM is to examine a set of relationships between one or more Independent Variables (IV) and one or more Dependent Variables (DV).



Fan et al. 2016

Introduction

- Both IV's and DV's can be continuous or discrete.
- Independent variables are usually considered either predictor or causal variables because they predict or cause the dependent variables (the response or outcome variables).

Introduction

- Genetics S. Wright (1921): *"Prior knowledge of the causal relations is assumed as prerequisite* … [in linear structural modeling]".

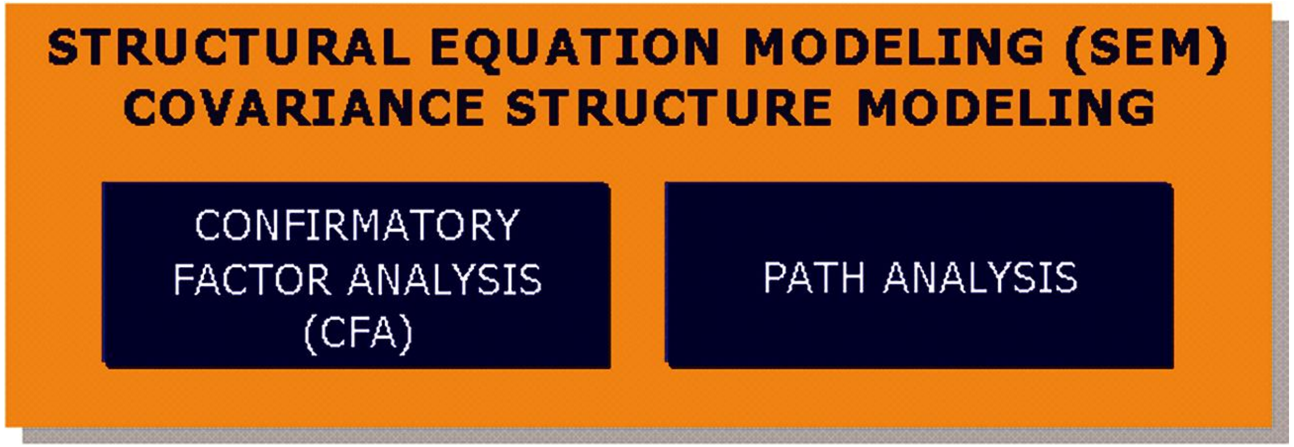
$$y = \beta x + \varepsilon$$

"In an ideal experiment where we control X to x and any other set Z of variables (not containing X or Y) to z, the value of Y is given by $\beta x + \varepsilon$, where ε is not a function of the settings x and z." (Pearl, 2000)

Introduction

- Two main components of SEM are presented in Figure 1.
  - CFA operates with observed and latent variables, path analysis operates only with observed variables.

Figure 1. Components of Structural Equation Modeling



(Nokelainen, 1999.)

Path Analysis

- Examines how *n* independent (x, IV, Xi, ξ) variables are statistically related to a dependent (y, DV, Eta, η) variable.
- Applies the techniques of regression analysis, aiming at more detailed resolution of the phenomena under investigation.
- Allows
  - *Causal* interpretation of statistical dependencies
  - Examination of how data fits to a theoretical model

Path Analysis

- Once the data is available, conduction of path analysis is straightforward:
  1. Draw a path diagram according to the theory.
  2. Conduct one or more regression analyses.
  3. Compare the regression estimates (B) to the theoretical assumptions or (Beta) other studies.
  4. If needed, modify the model by removing or adding connecting paths between the variables and redo stages 2 and 3.

Path Analysis

- Data assumptions:
  - DV:
    - Continuous, normally distributed (univariate normality assumption)
  - IV:
    - Continuous (no dichotomy or categorical variables)
  - N:
    - About 30 observations for each IV

Path Analysis

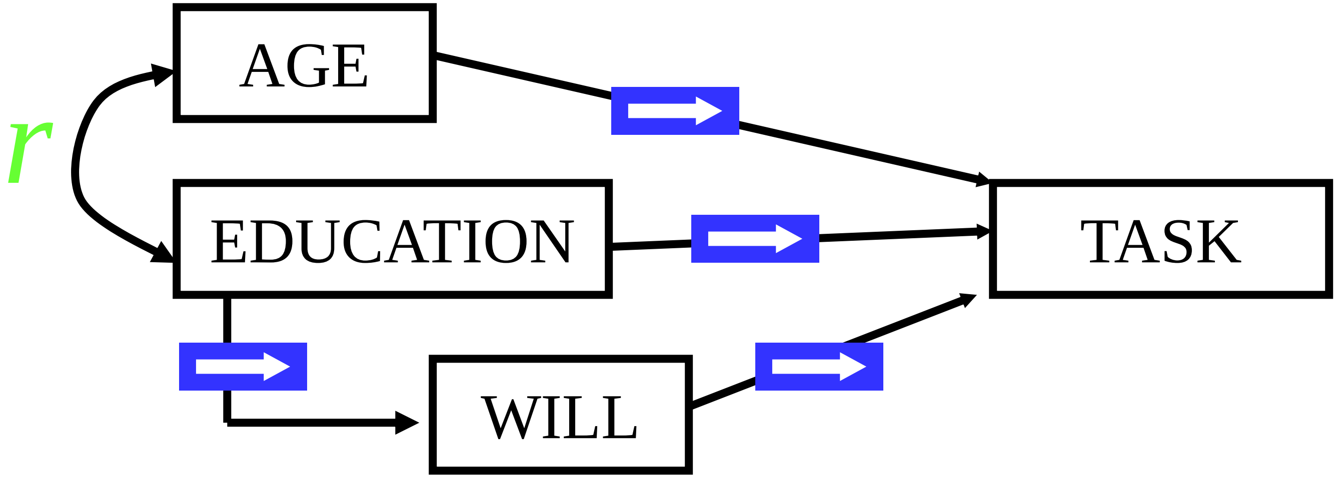
- Theoretical assumptions
  - Causality:
    - X_1 and Y_1 correlate.
    - X_1 precedes Y_1 chronologically.
    - X_1 and Y_1 are still related after controlling other dependencies.
- Statistical assumptions
  - Model needs to be recursive.
  - It is OK to use ordinal data.
  - All variables are measured (and analyzed) without measurement error ($\varepsilon = 0$).

Path Analysis

- As stated earlier, path analysis assumes that the model is recursive.
  - Nature of causal dependency is unidirectional, like a ’one way road’ (arc with one head →).
  - If there is no a priori information available about the direction of causal dependency, it is assumed to be correlational (arc with two heads ↔).

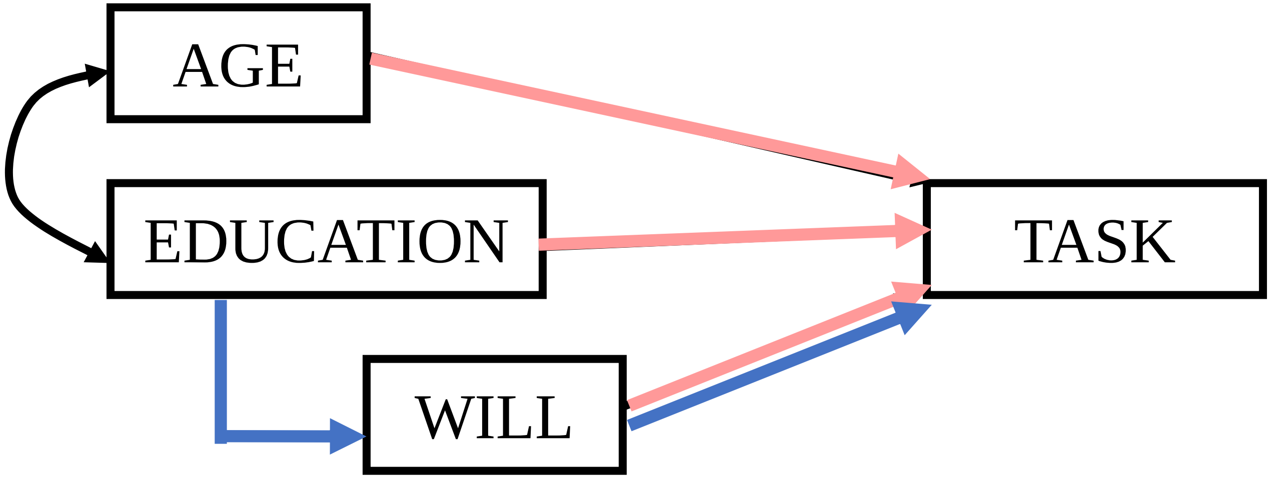
r

Path Analysis



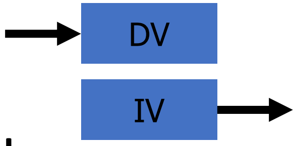
Path Analysis

- Direct and indirect effect



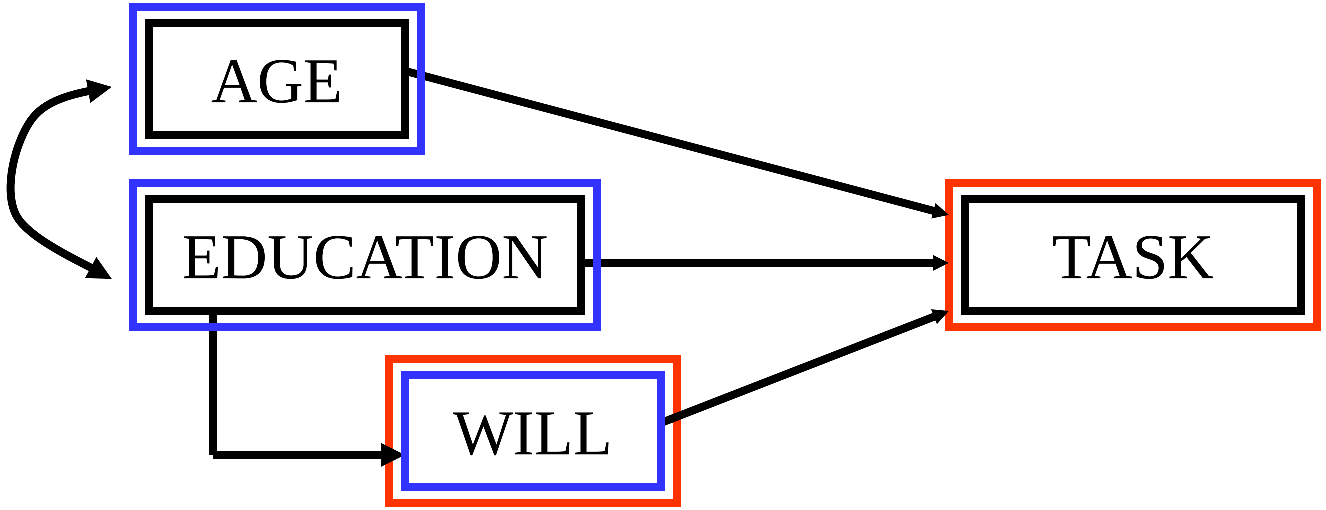
Path Analysis

- There are two types of observed variables:
  - Endogenous (y, DV, Eta η).
  - Exogenous (x, IV, Xi ξ).
- For each endogenous (DV) variable, a regression analysis is performed.



Path Analysis

x IV Xi ξ EXOGENIOUS
y DV Eta η ENDOGENIOUS



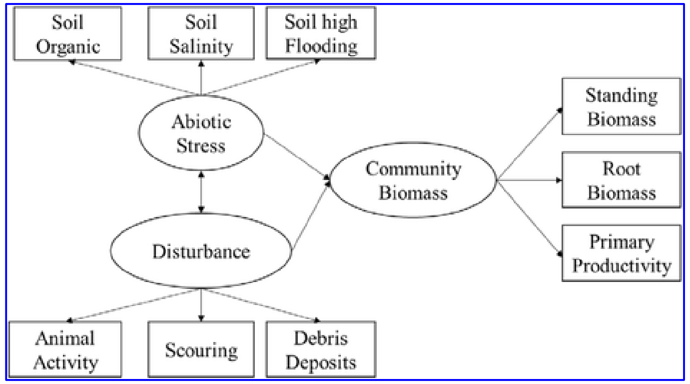
Two regression analyses:
1) AGE + EDUCATION + WILL -> TASK
2) EDUCATION –> WILL

Path Analysis

- Path coefficient ($p_{DV,IV}$) indicates the direct effect of IV to DV.
- If the model contains only one IV and DV variable, the path coefficient equals to correlation coefficient.
  - In those models that have more than two variables (one IV and one DV), the path coefficients equal to partial correlation coefficients.
    - The other path coefficients are controlled while each individual path coefficient is calculated.

Basic Concepts of Factor Analysis

- The fundamental idea underlying the factor analysis is that some but not all variables can be directly observed.
- Those unobserved variables are referred to as either *latent* variables or factors.
- Information about latent variables can be gained by observing their influence on observed variables.
- Factor analysis examines covariation among a set of observed variables trying to *generate a smaller number of latent variables*.



Fan et al. 2016

Basic Concepts of Factor Analysis

- ***Exploratory Factor Analysis***
  - In exploratory factor analysis (EFA), observed variables are represented by squares and circles represent latent variables.
  - Causal effect of the latent variable on the observed variable is presented with straight line with arrowhead.

Basic Concepts of Factor Analysis

- ***Exploratory Factor Analysis***
  - The latent factors (ellipses) labeled with ξ's (Xi) are called common factors and the δ's (delta) (usually in circles) are called errors in variables or *residual variables*.
  - Errors in variables have unique effects to one and only one observed variable - unlike the common factors that share their effects in common with more than one of the observed variables.

Basic Concepts of Factor Analysis

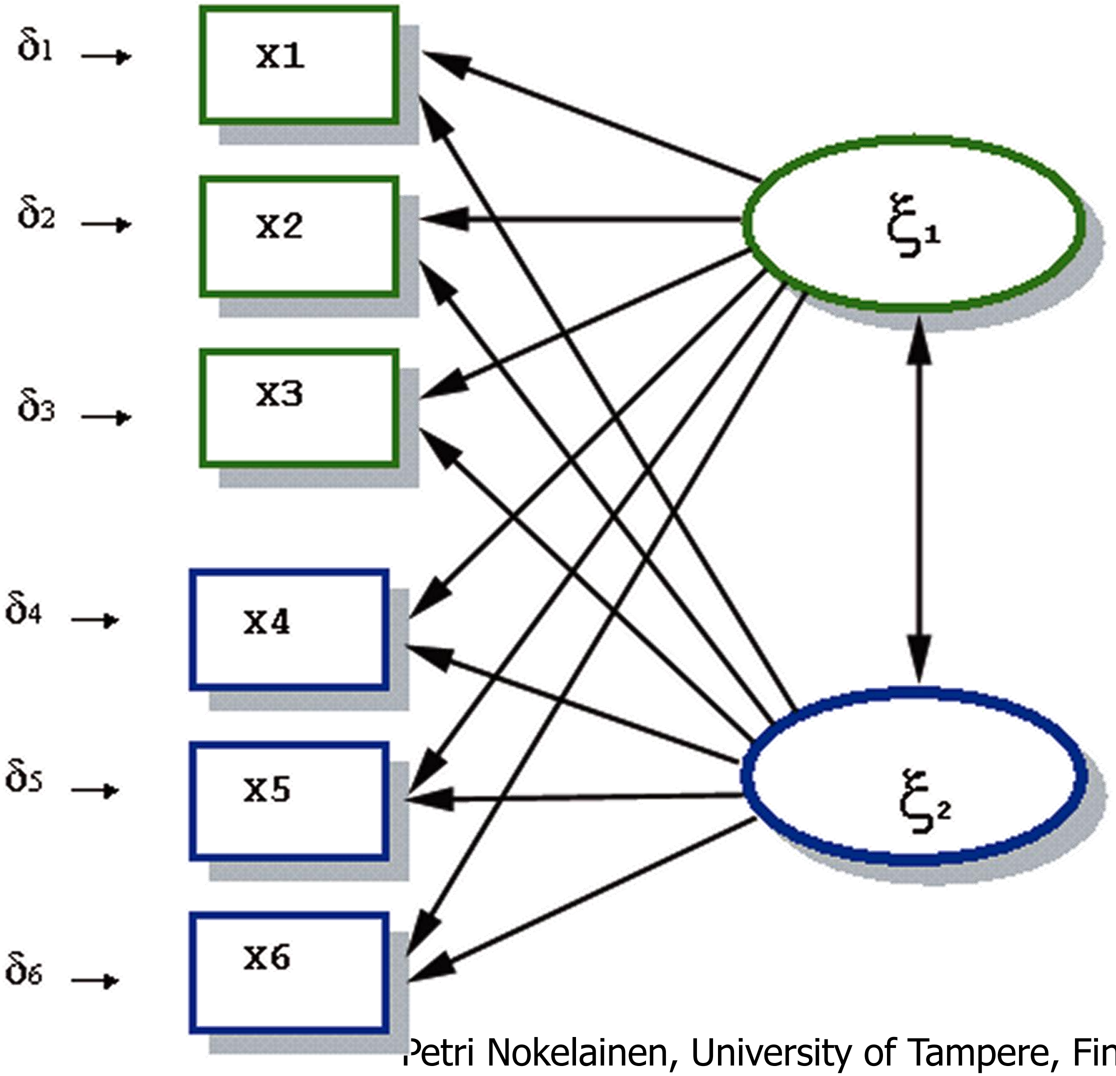


Figure 2.
Exploratory Factor Model
(Nokelainen, 1999.)

Basic Concepts of Factor Analysis

- ***Exploratory Factor Analysis***
  - The EFA model in Figure 2 reflects the fact that researcher does not specify the structure of the relationships among the variables in the model.
  - When carrying out EFA, researcher must assume that
    - all common factors are correlated,
    - all observed variables are directly affected by all common factors,
    - errors in variables are uncorrelated with one another,
    - all observed variables are affected by a unique factor and
    - all ξ's are uncorrelated with all δ's. (Long, 1983.)

Basic Concepts of Factor Analysis

- ***Confirmatory Factor Analysis***
  - One of the biggest problems in EFA is its inability to incorporate substantively meaningful constraints.
  - That is due to fact that algebraic mathematical solution to solve estimates is not trivial, instead one has to seek for other solutions.
  - That problem was partly solved by the development of the confirmatory factor model, which was based on an iterative algorithm (Jöreskog, 1969).

Basic Concepts of Factor Analysis

- ***Confirmatory Factor Analysis***
  - In confirmatory factor analysis (CFA), which is a special case of SEM, the correlations between the factors are an explicit part of the analysis because they are collected in a matrix of factor correlations.
  - With CFA, researcher is able to decide *a priori* whether the factors would correlate or not. (Tacq, 1997.)

Basic Concepts of Factor Analysis

- ***Confirmatory Factor Analysis***
  - Moreover, researcher is able to impose substantively motivated constraints,
    - which common factor pairs that are correlated,
    - which observed variables are affected by which common factors,
    - which observed variables are affected by a unique factor and
    - which pairs of unique factors are correlated.
      (Long, 1983.)

Basic Concepts of Factor Analysis

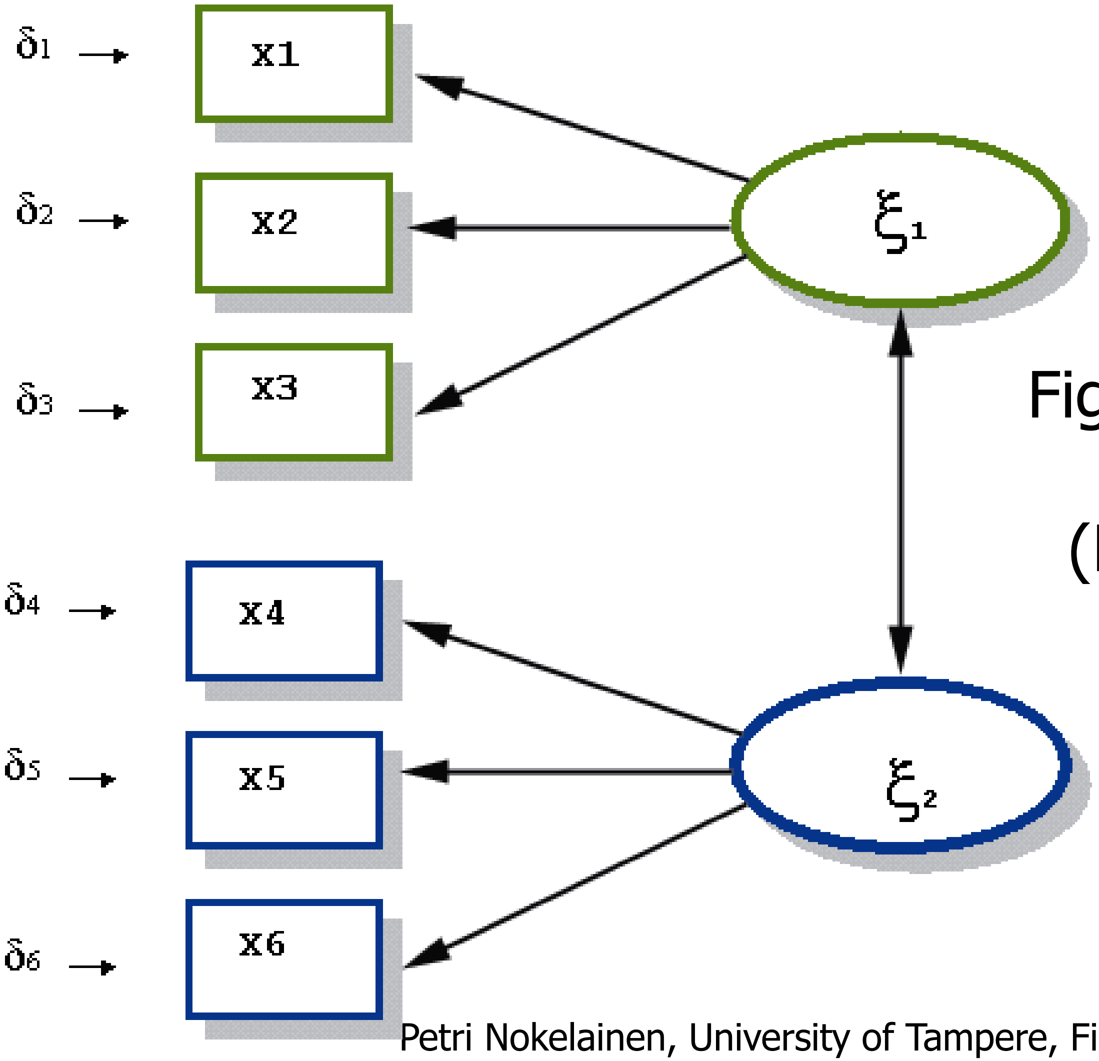


Figure 3. Confirmatory Factor Model (Nokelainen, 1999.)

Model Constructing

- In this presentation, I will use both the LISREL 8 –software and AMOS 5 for SEM analysis and PRELIS 2 –software (Jöreskog et al., 1985) for preliminary data analysis.
- All the previously mentioned approaches to SEM use the same pattern for constructing the model:
  1. model hypotheses,
  2. model specification,
  3. model identification and
  4. model estimation.

1. Model Hypotheses

Table 1. Variable Description

	Item	Summary variable	Sample statement
SUPPORTIVE MANAGEMENT	X1	Participative Leadership	It is easy to be touch with the leader of the training programme.
	X2	Elaborative Leadership	This organization improves it's members professional development.
	X3	Encouraging Leadership	My superior appreciates my work.
FUNCTIONAL GROUP	X4	Collaborative Activities	My teacher colleagues give me help when I need it.
	X5	Teacher – Student Connections	Athmosphere on my lectures is pleasant and spontaneous.
	X6	Group Spirit	The whole working community co-operates effectively.

1. Model Hypotheses

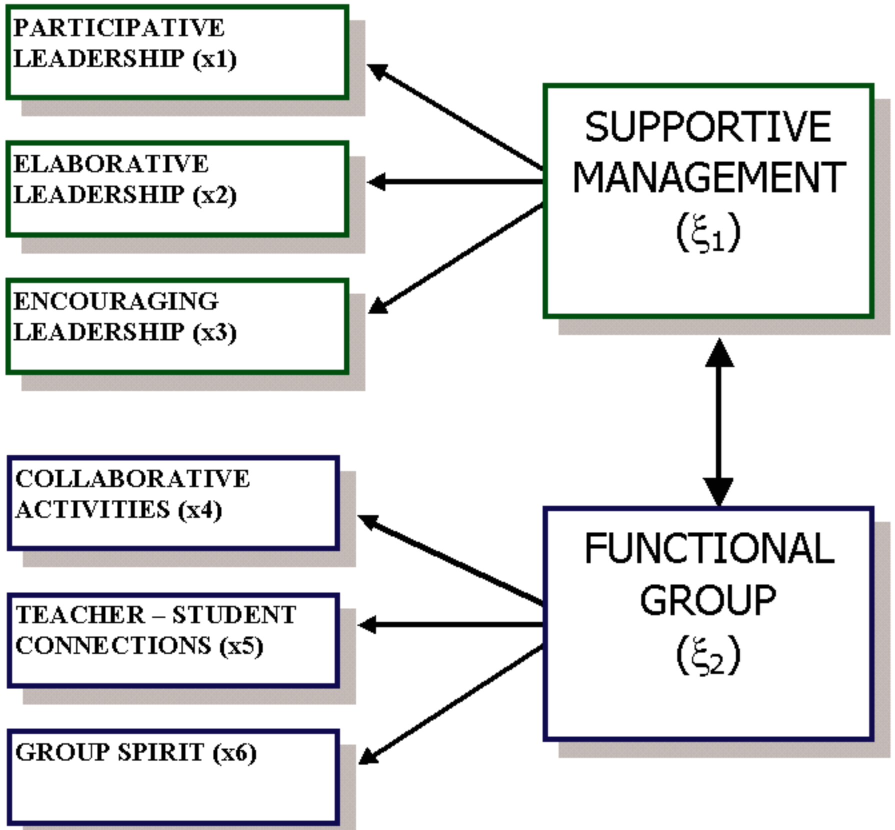
- A sample of the data is presented in Table 2.

Table 2. A Sample of the Raw Data Set

	Variables					
	Supportive Management			Functional Group		
Teachers	Participative Leadership (x1)	Elaborative Leadership (x2)	Encouraging Leadership (x3)	Collaborative Activities (x4)	Teacher-student Connections (x5)	Group Spirit (x6)
1.	2.75	3.25	4.00	2.60	3.00	2.00
2.	3.25	3.75	5.00	3.40	4.00	3.00
3.	3.50	3.75	4.00	3.60	4.75	3.00
. . .						
319	5.00	1.00	3.00	3.00	3.00	5.00

1. Model Hypotheses

Figure 4. Hypothesized Model

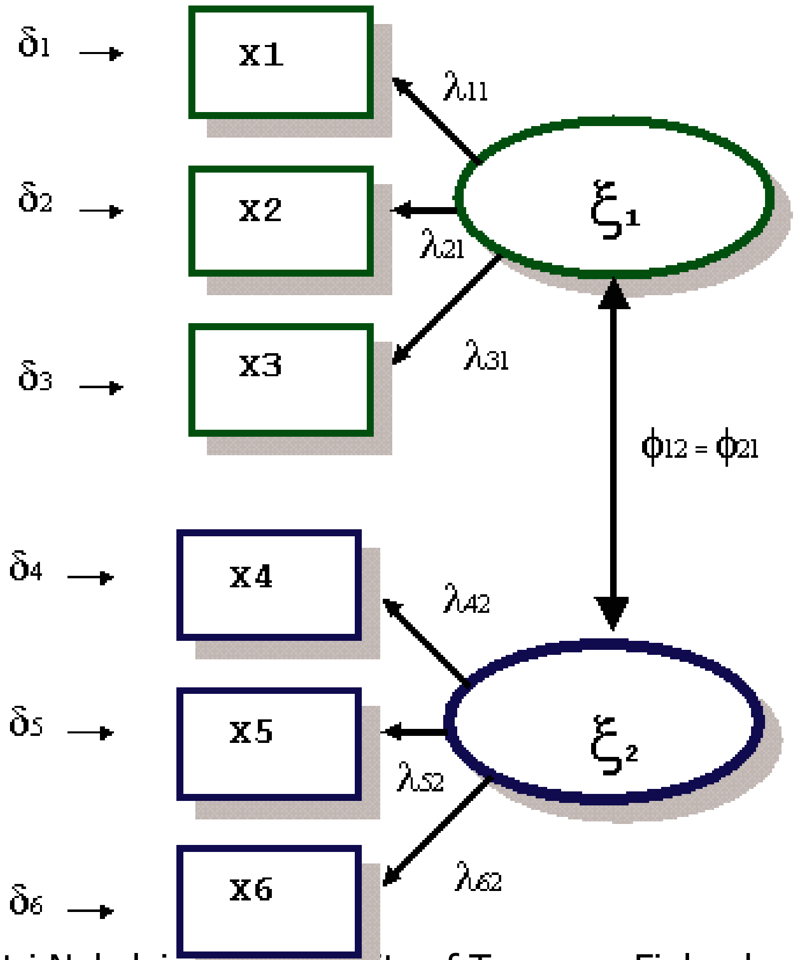


1. Model Hypotheses

- Two main hypotheses of interest are:
  - Does a two-factor model fit the data?
  - Is there a significant covariance between the supportive and functional factors?

2. Model Specification

Figure 5. Measurement Model



2. Model Specification

- Specification of the confirmatory factor model requires making formal and explicit statements about
  - the number of common factors,
  - the number of observed variables,
  - the variances and covariances among the common factors,
  - the relationships among observed variables and latent factors,
  - the relationships among residual variables and
  - the variances and covariances among the residual variables. (Jöreskog et al., 1989.)

3. Model Identification

- Identification is a theoretical property of a model, which depends neither on data or estimation.
  - When our model is identified we obtain unique estimates of the parameters.
- “Attempts to estimate models that are not identified result in arbitrary estimates of the parameters.” (Long, 1983, p. 35.)

3. Model Identification

- We gain constantly an identified model if
  - each observed variable in the model measures only one latent factor and
  - factor scale is fixed (Figure 6) or one observed variable per factor is fixed (Figure 7). (Jöreskog et al., 1979, pp. 196-197; 1984.)

4. Model Estimation

- When identification is approved, estimation can proceed.
- If the observed variables are normal and linear and there are more than 100 observations (319 in our example), Maximum Likelihood estimation is applicable.

4. Model Estimation

Figure 4. Hypothesized Model

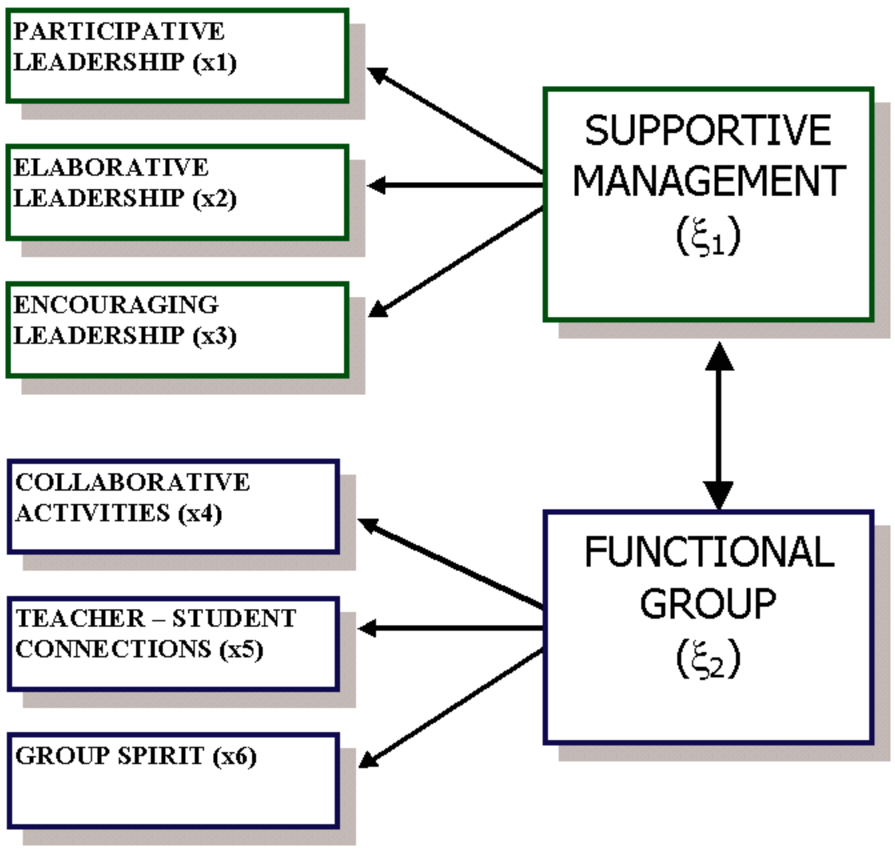
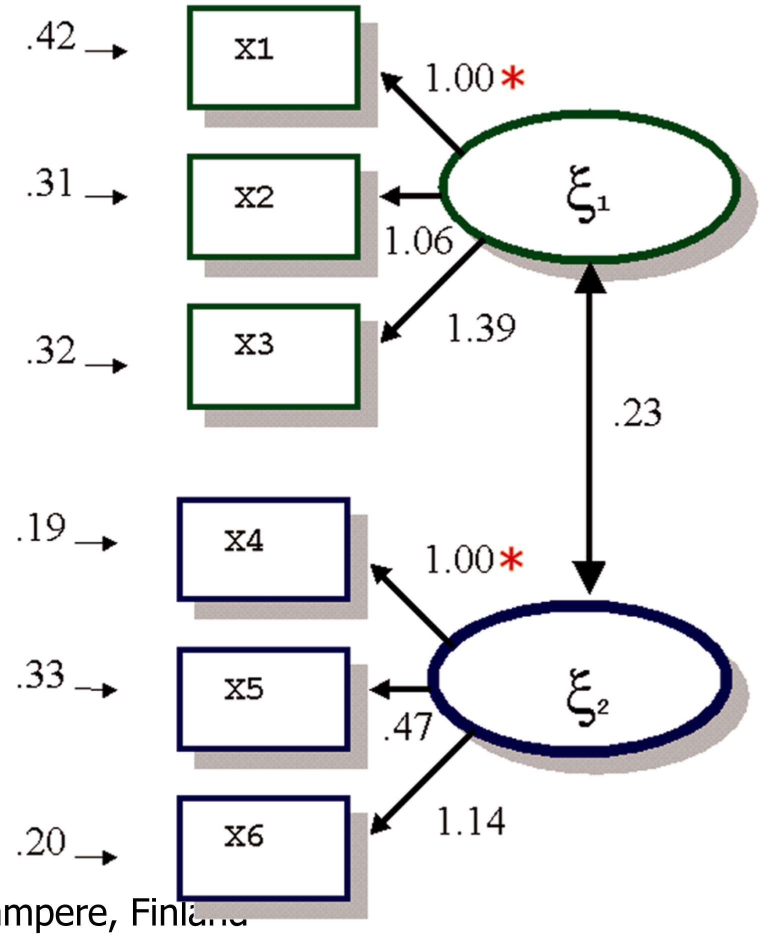


Figure 9. Parameter Estimates



Conclusions

- SEM has proven to be a very versatile statistical toolbox for educational researchers when used to confirm theoretical structures.
- Perhaps the greatest strength of SEM is the requirement of a prior knowledge of the phenomena under examination.
    - In practice, this means that the researcher is testing a theory which is based on an exact and explicit plan or design.
    - One may also notice that relationships among factors examined are free of measurement error because it has been estimated and removed, leaving only common variance.
    - Very complex and multidimensional structures can be measured with SEM; in that case SEM is the only *linear* analysis method that allows complete and simultaneous tests of all relationships.

Conclusions

- Disadvantages of SEM are also simple to point out.
  - Researcher must be very careful with the study design when using SEM for *exploratory* work.
  - As mentioned earlier, the use of the term ‘causal modeling’ referring to SEM is misleading because there is nothing causal, in the sense of inferring causality, about the use of SEM.
  - SEM's ability to analyze more complex relationships produces more complex models: Statistical language has turned into jargon due to vast supply of analytic software (LISREL, EQS, AMOS).
  - When analyzing scientific reports methodologically based on SEM, usually a LISREL model, one notices that they lack far too often decent identification inspection which is a prerequisite to parameter estimation.

Conclusions

- Overgeneralization is always a problem – but specifically with SEM one must pay extra attention when interpreting causal relationships since *multivariate normality* of the data is assumed.
  - This is a severe limitation of linear analysis in general because the reality is seldom linear.
- We must also point out that SEM is based on covariances that are not stable when estimated from small (<200 observation) samples.
- On the other hand, too large (>200 observations) sample size is also a reported problem (e.g., Bentler et al., 1983) of the significance of χ^2.

Conclusions

- SEM programs allow calculation of modification indices which help researcher to fit the model to the data.
  - Added or removed dependencies must be based on theory!
  - Overfitting model to the data reduces generalizability!
- Following slides demonstrate the effect of sample size and model modification (according to modification indices).
  - Example 2 in the course exercise booklet.

SEM applications in SES research

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Applications of structural equation modeling (SEM) in ecological studies: an updated review

Yi Fan, Jiquan Chen, Gabriela Shirkey, Ranjeet John, Susie R. Wu, Hogeun Park & Changliang Shao

Ecological Processes **5**, Article number: 19 (2016) | Cite this article

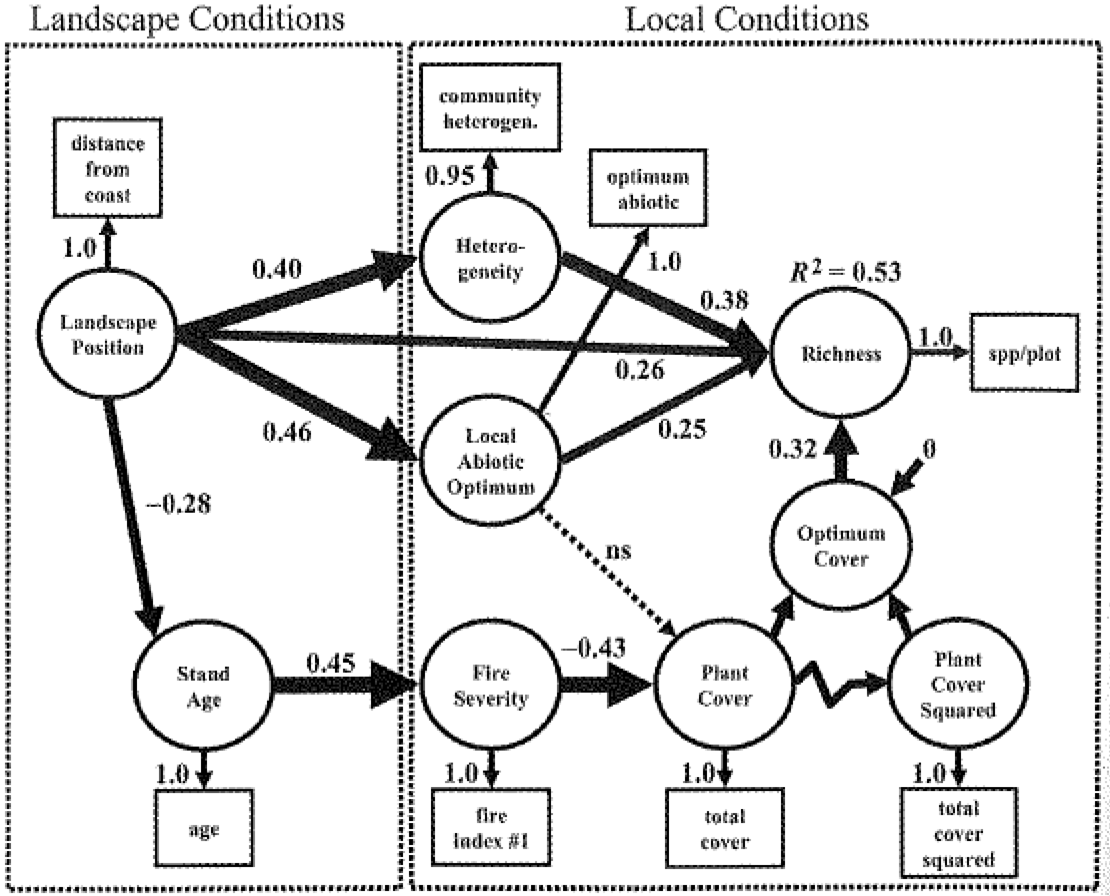
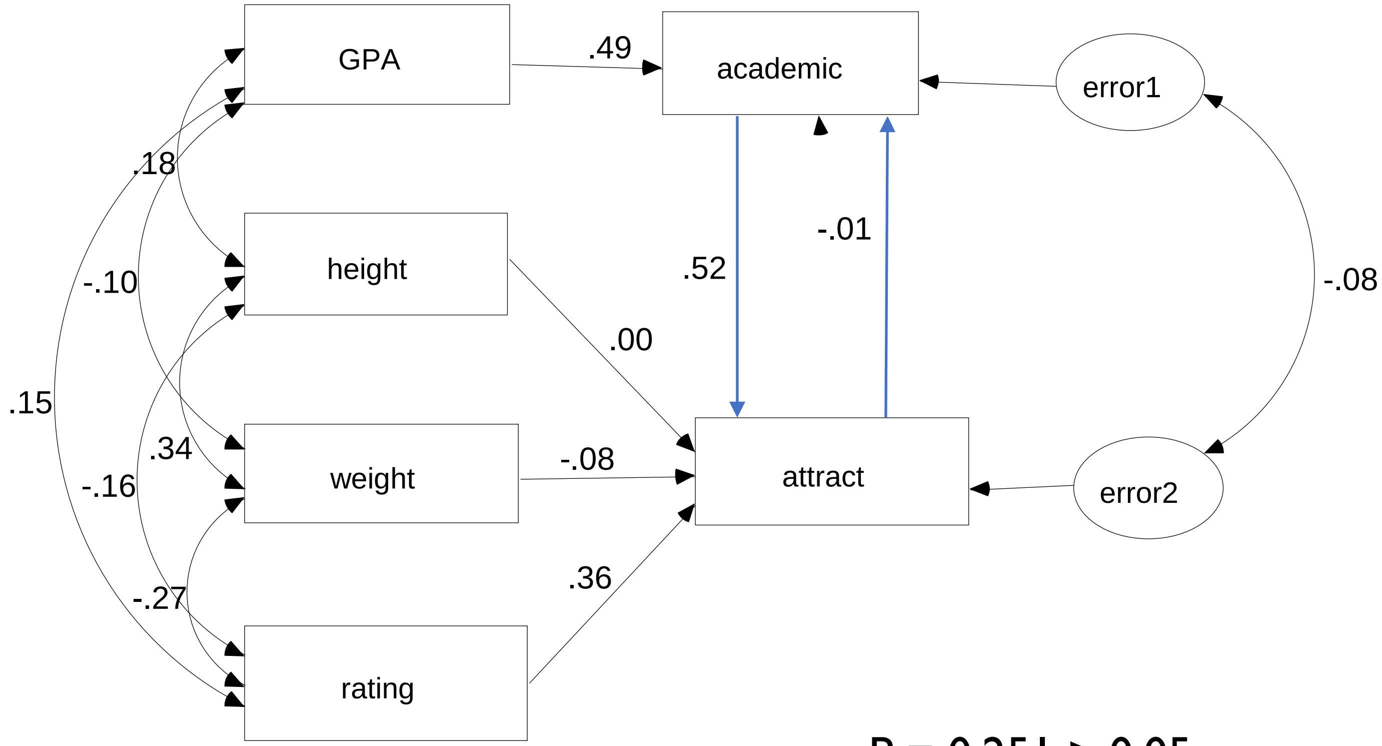


Figure 7.5. Relationship between herbaceous richness and various factors following fire in southern California chaparral (from Grace and Keeley 2006). This model includes an explicit nonlinearity between Plant Cover and Richness, along with a composite variable summarizing the relationship called Optimum Cover.

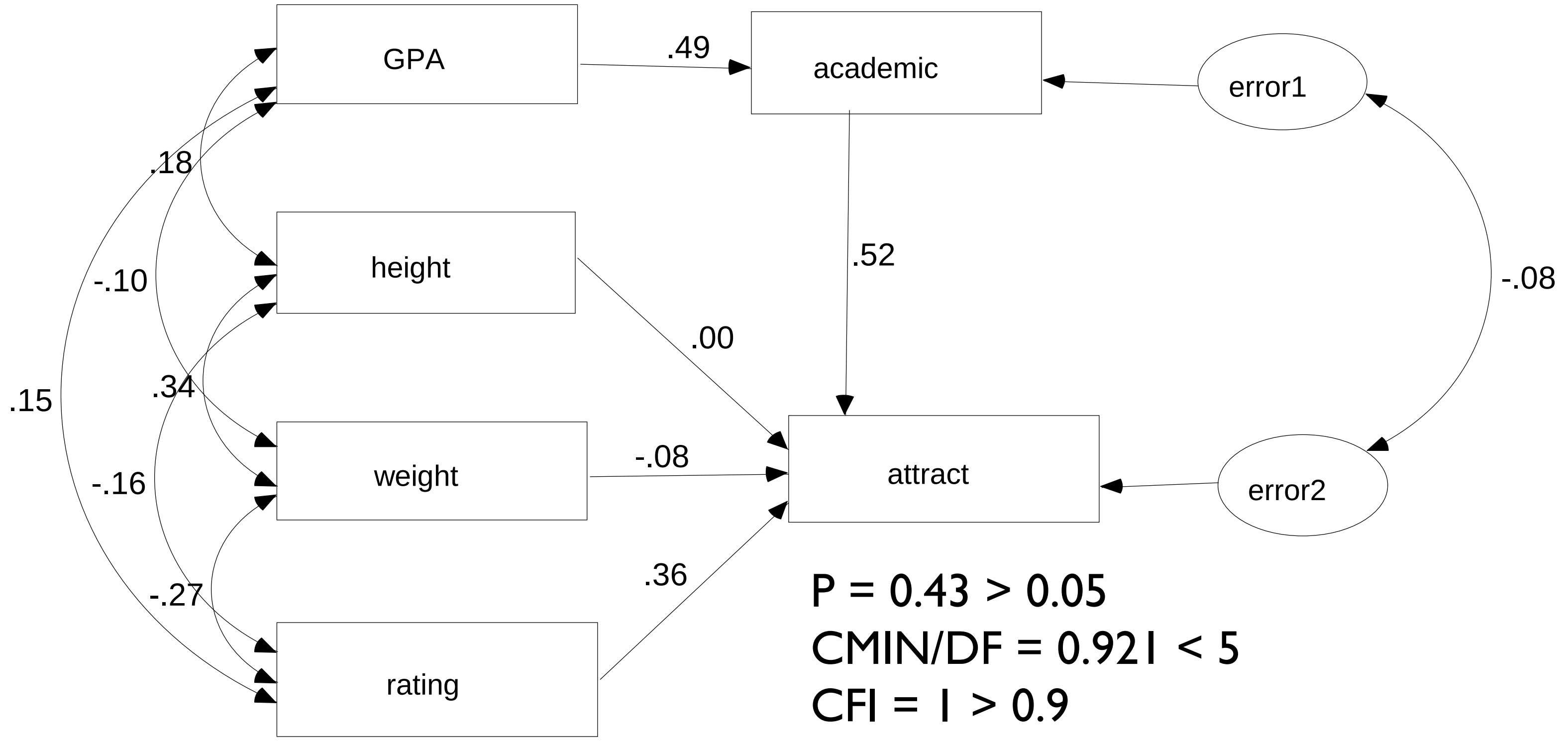
Grace. 2006

Model A



P = 0.251 > 0.05
CMIN/DF = 1.381 < 5
CFI = 0.996 > 0.9
NFI = 0.988 > 0.8
RMSEA = 0.043 < 0.06
Conclusion: Model is accepted

Model B: Respecification

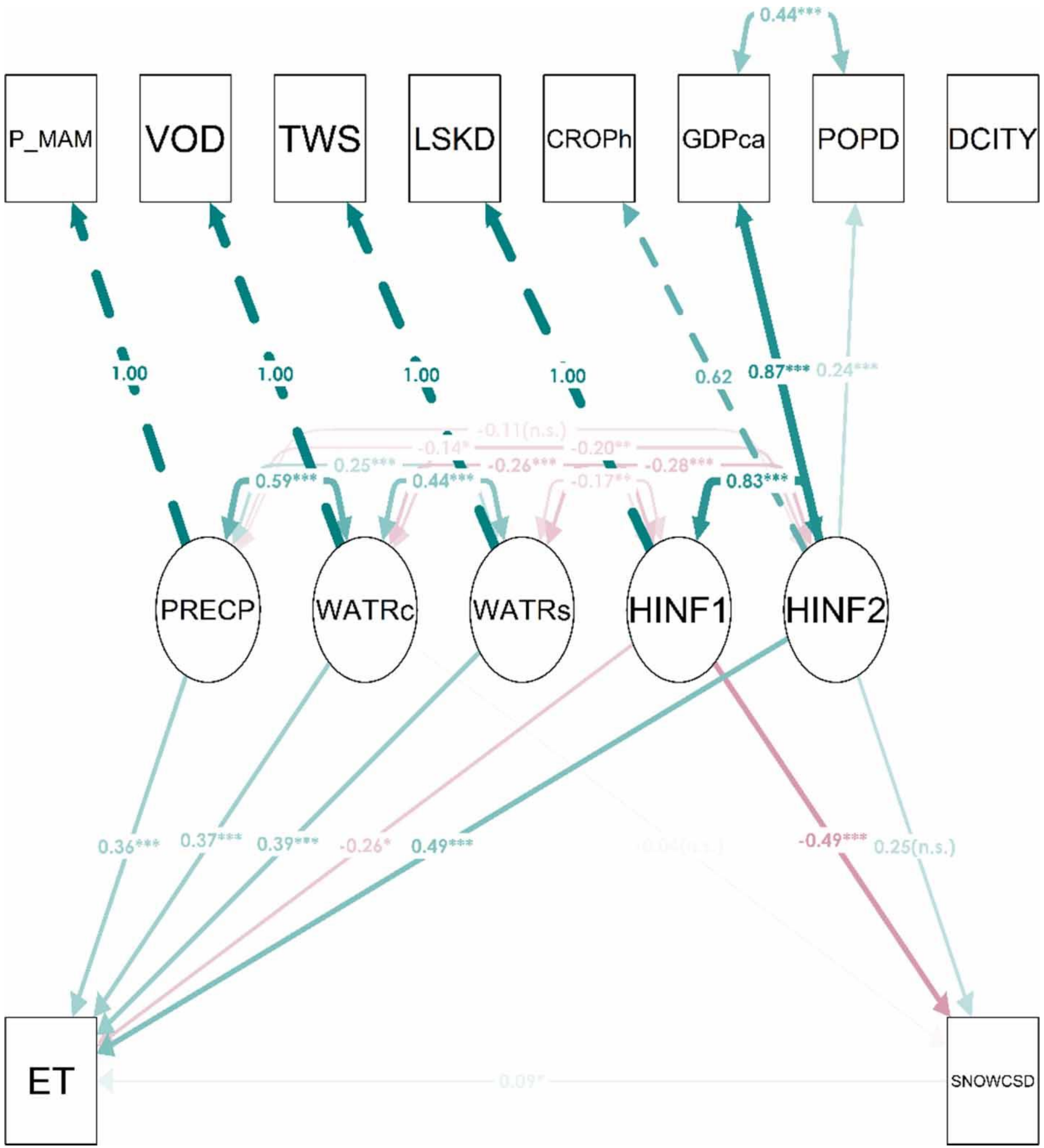


P = 0.43 > 0.05
CMIN/DF = 0.921 < 5
CFI = 1 > 0.9
NFI = 0.988 > 0.8
RMSEA = 0.000 < 0.06
Conclusion: Model is accepted

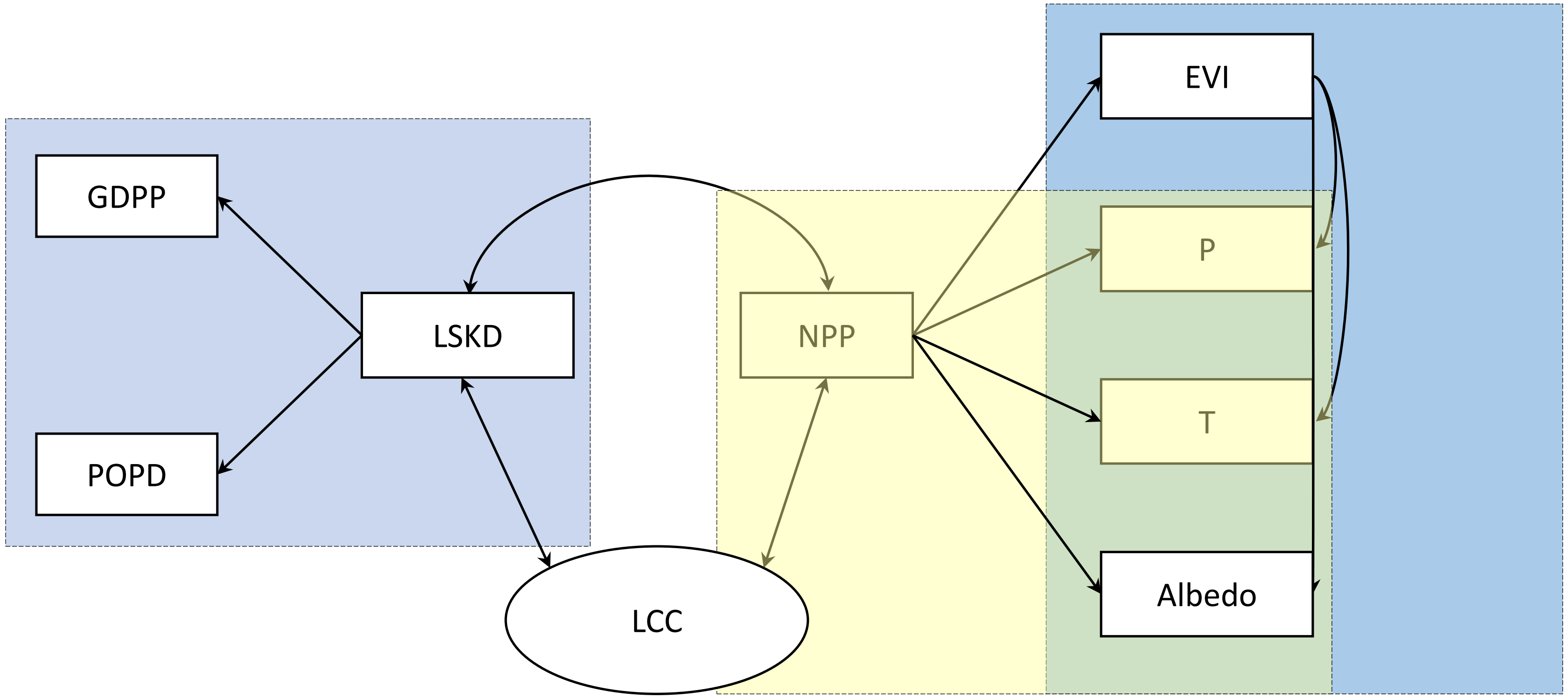
Model B is better than Model A

Figure 7. Structural equation modeling examining percent snow cover variability ($SNOWc_{SD}$) as a moderator between the evapotranspiration (ET) and precipitation (PRECP), water content (WATRc), water storage (WATRs), human influence—1 (HINF1) and human influence—2 (HINF2) as constructs (i.e. latent variables). Model fit—chi-square (χ^2; degrees of freedom = 19) = 55.26, comparative fit index = 0.96; Tucker–Lewis index = 0.90; standardized root mean square residual = 0.07. All parameter estimates are standardized (full forms in appendix)

Venkatesh et al. 2022



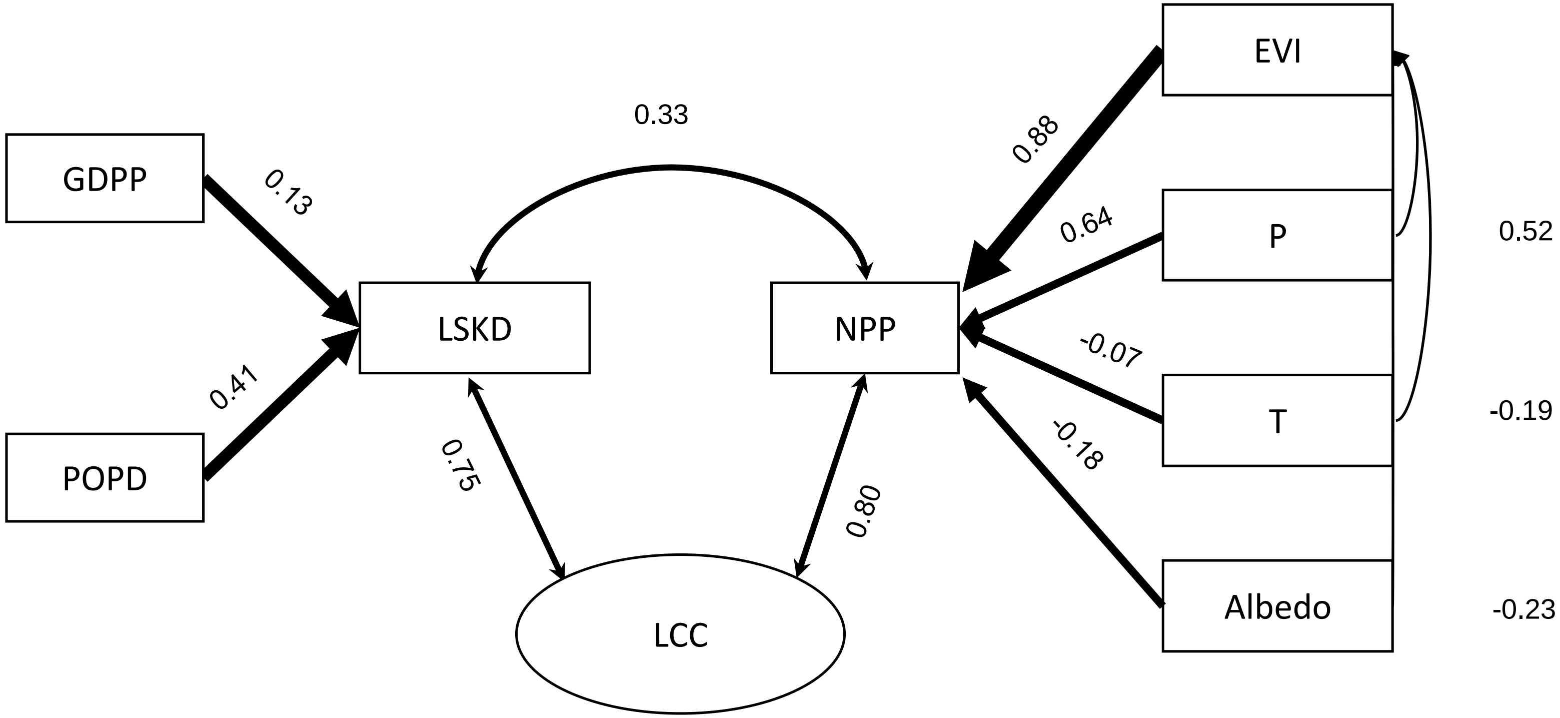
Hypothesis:
Structural Equation Modeling (SEM)



Chen et al. ERL, 2015

Mongolia Plateau

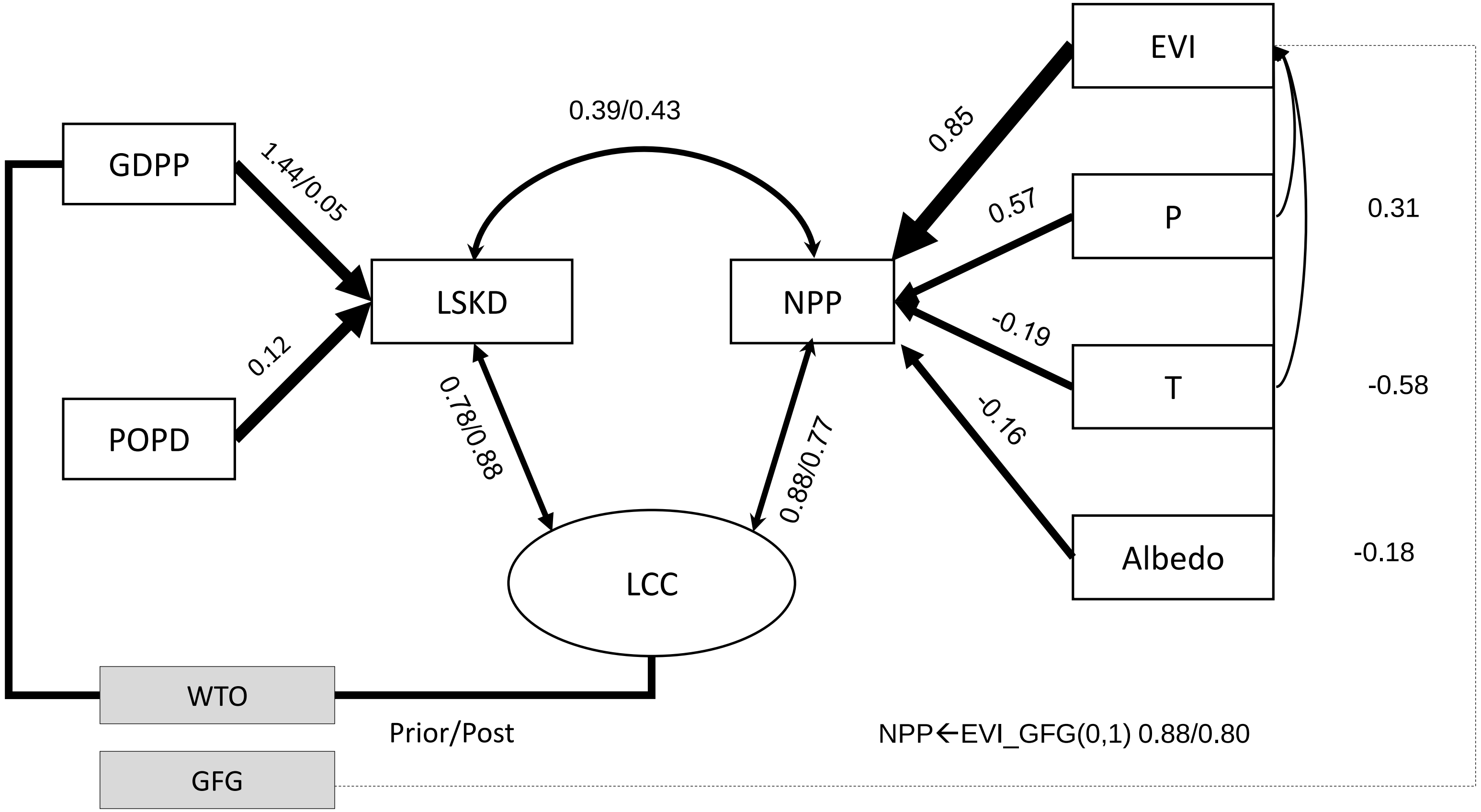
The Structural Equation Modeling of the CNH system



Chen et al. ERL, 2015

Mongolia Plateau

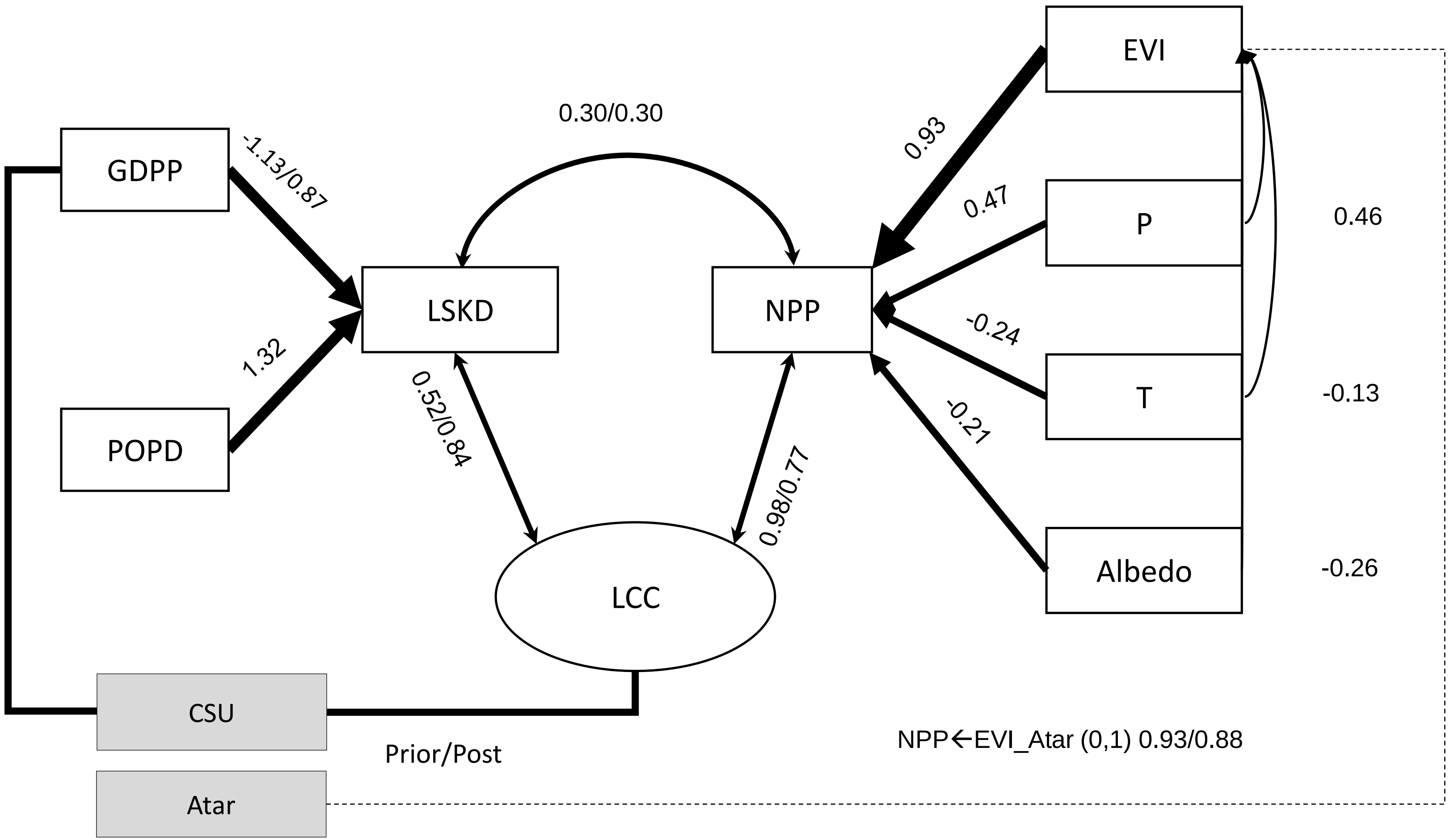
The Structural Equation Modeling of the CNH system



Chen et al. ERL, 2015

Mongolia Plateau

The Structural Equation Modeling of the CNH system



Chen et al. ERL, 2015

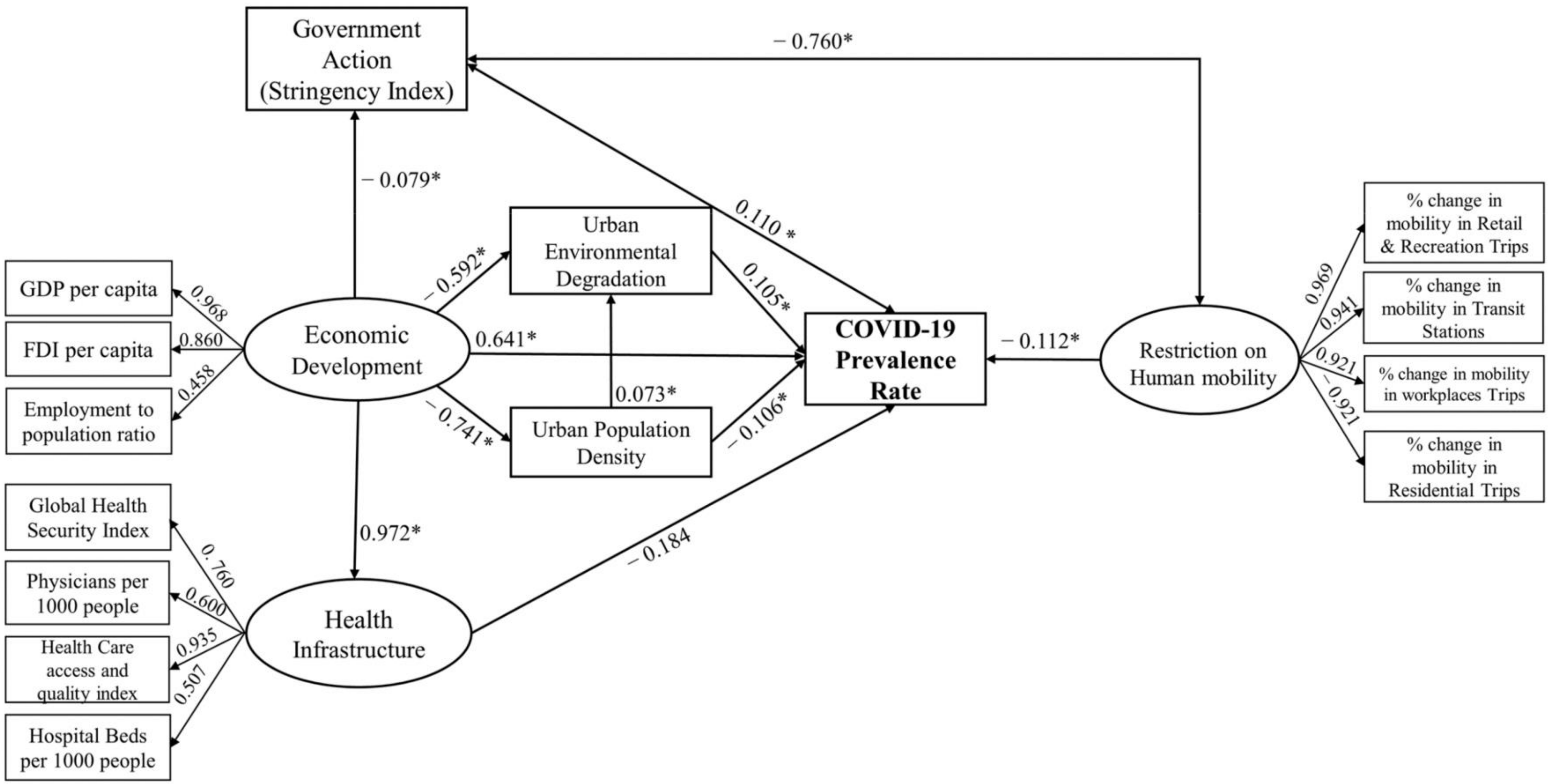


Figure 3. Empirical influences of major human system factors (economic, social, policy, health infrastructure, and urban environment status) on the prevalence rate (PR) of COVID-19 for the 151 countries from the 20-week study period. Observed variables are presented by boxes, latent variables by ovals and the standardized path coefficients and factor loads are listed next to arrows in the PLS-SEM model. The PR of COVID-19 was particularly related to economic development level, health infrastructure, and policies regarding restrictions on human mobility, but less associated with urban environment and urban population density. Fan et al. 2022.

Fig. 5. Partial Least Squares Structural Equation Modeling (PLS-SEM) of socioeconomic and biophysical drivers on urbanization in both Inner Mongolia (IM) and Mongolia (MG). Latent variables are circular shapes, and measured variables are squares. The path coefficients describe the relationship between variables. The IM model illustrates that the economy is a major driver of urbanization (R^2 = 0.422) whereas the MG model demonstrates that both economy and social goods drive urbanization (R^2 = 0.342).

Park et al. 2017

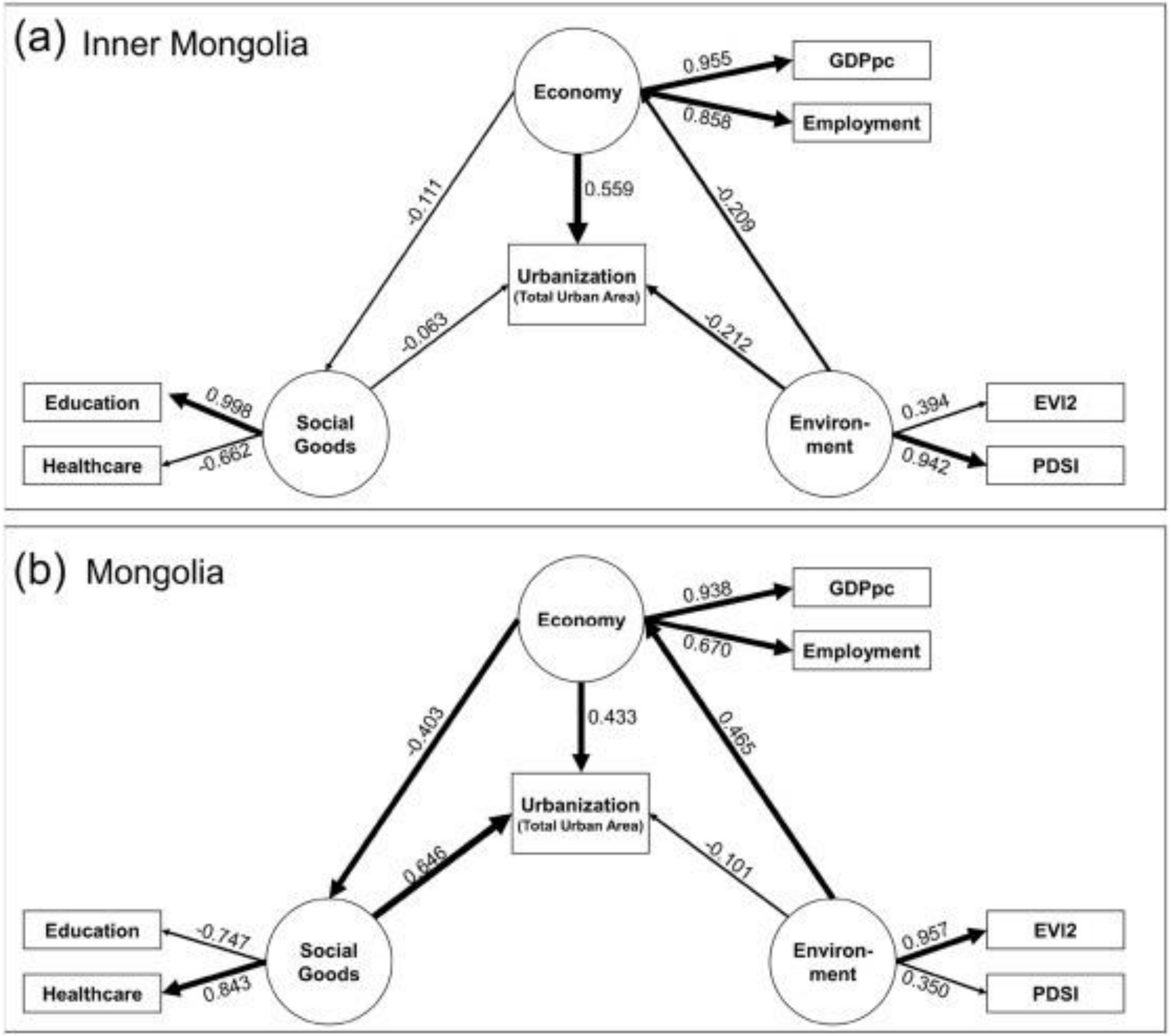
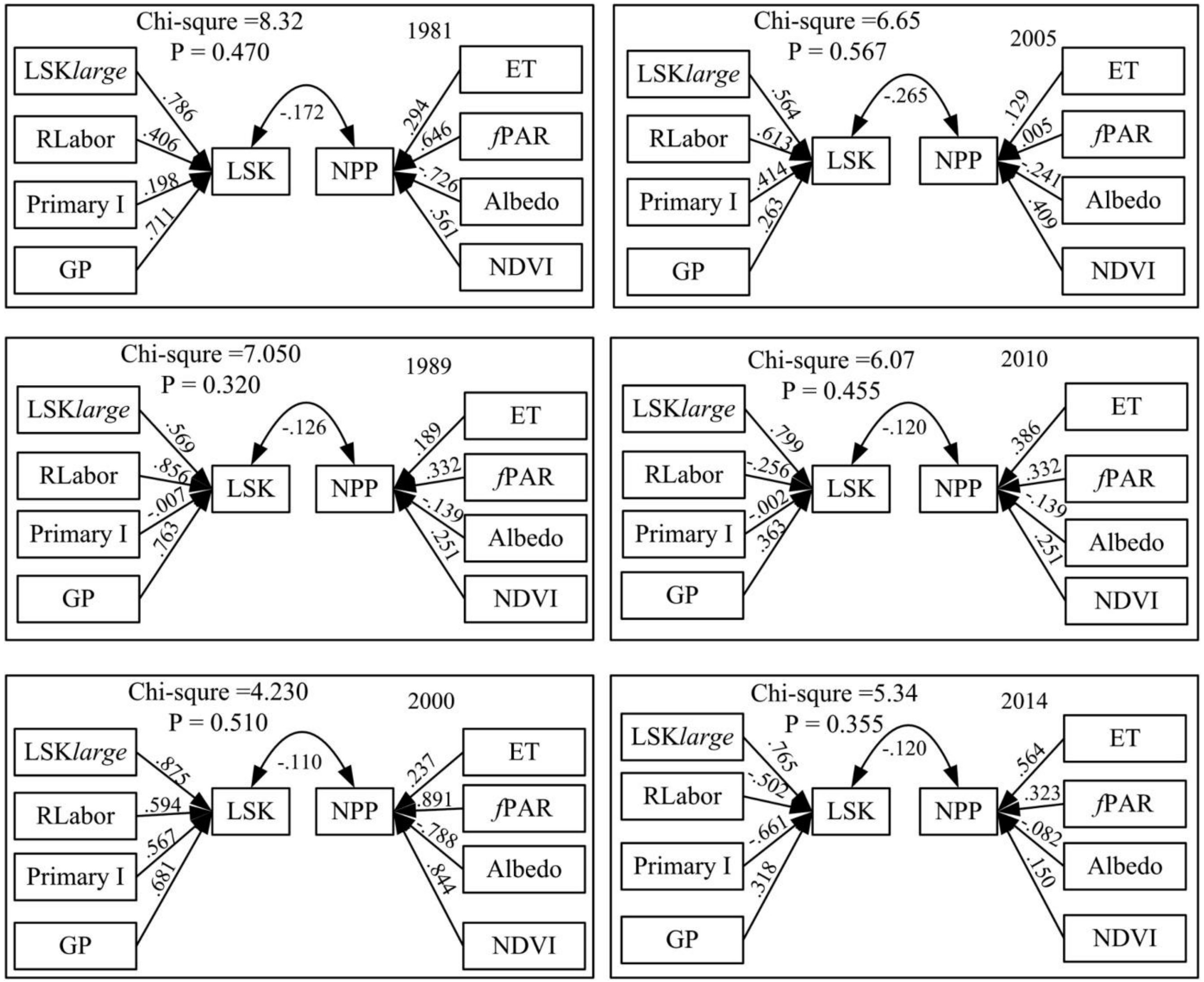


Figure 7. Dynamics of structural relationships based on structural equation modeling (SEM) for coupled changes of socioeconomic and environmental variables for the six time periods (1981, 1989, 2000, 2005, 2010, 2014) on the Tibetan Plateau. A one-way arrow indicates a hypothesized causal relationship between the two variables, while a two-way arrow indicates a feedback relationship. Absence of a line between any two variables implies that no hypothesis was proposed in this study. Livestock (LSK) is hypothesized to be influenced by LSK_{large}, R_{Labor}, Primary I, and GP, while ecosystem net primary productivity (NPP) is related to NDVI, *f*PAR, ET and Albedo (see figure 3). The residuals of LSK and NPP were assessed by the model. The partial regression coefficients indicated the strength and direction of these relationships.



Tian et al., 2018. Coupled dynamics of socioeconomic and environmental systems in Tibet. ERL.