# **Systems-Based Approach to the Analyses of Plant Functions: Conceptual Understanding, Implementation, and Analysis**

**Brijesh Singh Yadav, Amit Kumar Singh, and Sandeep K. Kushwaha**

#### **Contents**



# **1 Introduction of Plant Systems Biology**

Plant structure and function is a complex biological system determined by its molecular constituents such as DNA, RNA, proteins, metabolites, and macro- and microelements. Plants are enormously investigated in various aspects, like molecular genetics, breeding, genomics, and proteomics; however, we still have limited knowledge about plant genetic architecture and functioning mechanisms. Various solitary and mixed approaches have been developed in the past decades which have enhanced our knowledge about the role of genetics in plant. But, a holistic research approach requires a complete understanding of the plant structure and function at the molecular level which needs a lot of computational resources, different kinds of data generation, and integration algorithmic approaches (Sheth and Thaker [2014\)](#page-26-0). The most widely identified challenges are the data integration and management of large datasets from various sources such as genomic sequences, phenotype images,

B.S. Yadav  $(\boxtimes)$ 

#### S.K. Kushwaha Department Plant Breeding, Swedish University of Agriculture Sciences, Alnarp, Sweden

K.R. Hakeem et al. (eds.), *Plant Bioinformatics*, [https://doi.org/10.1007/978-3-319-67156-7\\_2](https://doi.org/10.1007/978-3-319-67156-7_2)

Department of Bioengineering, The University of Information Science and Technology (UIST), St. Paul, Republic of Macedonia e-mail: [brijeshbioinfo@gmail.com](mailto:brijeshbioinfo@gmail.com)

A.K. Singh Department of Molecular Biology and Ecology of Plants, Tel Aviv University, Tel Aviv, Israel

<sup>©</sup> Springer International Publishing AG 2017 107

protein 3D structures, and -omics data. Data heterogeneity is another major challenge due to different data syntactic (formats, schemas, and query interfaces) and semantic (data formalisms and abstraction, scope-specific naming conventions and inconsistencies). The recent advancements of computational techniques, resources, and high-throughput sample processing technologies have broken the technical and implementation barriers and facilitated the evolution and integration of "-omics" fields such as genomics, transcriptomics, proteomics, metabolomics, and phenomics for the implementation of systems biology paradigm in plant science. A large number of comprehensive and quantitative datasets have been generated in numerous targeted and system-wide studies facilitating the development of databases, software, data formats, and multivariate approaches for the integration of multiomics data. The high-throughput genetic and molecular tactics adopted to generate -omics data that can be analyzed and used in mathematical and computational models for revealing the networks on a global scale in the same platform is termed as systems biology (Fig. [1](#page-1-0)). Systems biology approaches successfully categorized the key molecules and their roles in complex biological events in the recent period. It reveals the large complex set of transcription factor with protein, primary metabolite (carbohydrates and lipid), and secondary metabolite (glucosinolates, phenols, and many more) association which regulate physiology, growth and development, and response to the environment requires the identification of networks on a genome and proteome scale. These interactions can be either physical or functional and often can be inferred from available data (Yadav et al. [2016](#page-26-1); Malik et al. 2014).

<span id="page-1-0"></span>

**Fig. 1** Outline of systems biology approach

Systems biology-based approaches are applied to reconstruct and model metabolic networks which identify significant limiting steps in seed development of both monocot and dicot plants (Sreenivasulu and Wobus [2013\)](#page-26-2). A comparative coexpression network examines to fortitude the seed size—a significant yield-related characteristics (Sreenivasulu and Wobus [2013\)](#page-26-2). Malik et al. (2014) explored biological networks to study protein-carbohydrate interactions in plant lectins using glycan microarray data. The integrated systems and network methods have helped to understand the complex behaviors of nitrogen use efficiency (NUE) which provide modalities in the form of products, process, and practices for improving agricultural productivity (Bi et al. [2009\)](#page-24-0). While working on photosynthetic parameters, -omics-based investigations have generated huge amounts of proteomics and genomics data which has helped to identify important traits for the improvement of photosynthetic efficiency in crop plants (Bräutigam et al. [2014;](#page-24-1) Kanwal et al. [2013\)](#page-25-0). Systems-based studies on model plants characterized genes such as CIR1, RPS2, RPM1, WRKY31, MPK9, WRKY33, FLS2, RPS4, and RPP13 which play important roles in biotic stress tolerance (Carstens et al. [2014](#page-24-2); Chinchilla et al. [2007;](#page-24-3) Leal [2013\)](#page-25-1). Mishra et al. [\(2011](#page-25-2)) identified chlorotic toxin as a cyclodepsipeptide which affects many components of MAP kinase machinery, hypersensitive response, and systemic acquired response. Understanding the mechanisms of plant responses to multiple simultaneous abiotic stresses is therefore crucial in providing opportunities for the development of broad-spectrum stress-tolerant crops. Recently, cellular and metabolic response in abiotic stress was studied in *Arabidopsis* using systems biology and network approach (Yadav et al. [2016](#page-26-1)) which represents the effect of metabolites in osmotic, wound, genotoxic, drought, salinity, heat, and UV-B stresses.

# **2 High-Throughput Experimental Techniques in Plant Systems Biology**

Parallelization is the central theme of high-throughput experiment (HTE), which has featured to carry out many experiments simultaneously. High-throughput experimentation technique and methods have evolved significantly in the last two decades which enabled to probe the plant circadian clock, a key coordinator of vital biological processes for whole system and targeted studies.

### *2.1 DNA Microarray Technology*

Microarray allows to study the expression of thousands of genes simultaneously through the hybridization of probe sequences to nucleic acid sequences in mixture. In microarrays, probe sequences are fixed on solid surface and hybridizations are detected through fluorescent detection signal of labeled samples. Microarray technology was developed in the late 1970s and revolutionized in the beginning of new century due to high growth in genomic sequences, genomic sequencing projects, and availability of publicly curated and non-curated databases. Glass spotted arrays, in situ synthesized arrays, and self-assembled arrays are basic types of arrays used in the time frame (Bumgarner [2013\)](#page-24-4). Microarrays were used to measure gene expression levels and differential gene expression studies, comparison of expression patterns across samples, trait associations, etc. These studies improved our understanding of the cellular physiology and dynamics, interconnection of gene networks, and products for environmental input processing and phenotypic regulation which facilitates the global gene expression studies at systems level (Yamaguchi-Shinozaki and Shinozaki [2005;](#page-26-3) Chen and Zhu [2004\)](#page-24-5). Deciphering of gene network for soybean and *Arabidopsis* seed compartments from pre-globular to early maturation stage, seeds are the excellent and widely used examples of microarray application in plants genotyping ([http://seed](http://seedgenenetwork.net/)[genenetwork.net/](http://seedgenenetwork.net/)). Microarrays are used for single-nucleotide-polymorphism genotyping and most commonly used for allele discrimination by hybridization, allele-specific extension, and ligation (Hirschhorn et al. [2000\)](#page-25-3). Microarray is a popular technique because of its simple application and cost- and time-effective process which suits best for routine practice. Limitations of microarray technology are information of known sequences required for probe, no molecular resolution for hybridization, biased detection of novel and rare transcripts, constrain of hybridization, and relatively low specificity and sensitivity.

# *2.2 Next-Generation Sequencing (NGS)*

After microarray, there were revolutionary advances in DNA sequencing technologies with the advent of next-generation sequencing (NGS) techniques. As techniques and datasets continue to improve and grow, we are also rapidly moving to the point where every organism, not just selected "model organisms," is open to the power of NGS. For transcriptome analysis RNA sequencing is important because it can show the expressed sequences in specific tissues at a specific time and is rapidly replacing other methods for studying gene expression such as microarrays. For experimental setup it needs (1) organism-specific features, such as level of heterozygosity and availability of a reference genome and the consequences of organism choice on analysis; (2) tissue treatment and selection of tissue types to obtain the desired transcriptome and the desirability of replicates; (3) techniques for efficiently selecting transcripts for sequencing; (4) normalizing transcripts to avoid overrepresentation of highly abundant transcripts; (5) choice of sequencing platforms; and (6) methods of data assembly, with a useful table of assembly programs.

Evolution in DNA sequencing technologies has transformed the biological science research and outreach. In 1987, capillary electrophoresis-based first sequencing instrument, i.e., AB370, was introduced by Applied Biosystems, and a decade later, AB3730xl was introduced as "first-generation" working horse for highthroughput sequencing. From 2005, sequencing techniques have revolutionized and transformed into short read, massively parallel sequencing and established as the "next-generation" sequencing technique (Metzker [2010](#page-25-4)).

In early second generation sequencer, Roche 454 GS FLX+ pyrosequencer was well known for the sequencing of long read length (approx. 700 bp) and low output (approx. 1 Million reads/run). It was widely used for 16S variable region sequencing as well as targeted amplicon sequencing. Illumina reversible terminator sequencing is popular for versatile sequencing potential, i.e., read length (50–300 bp) and read number (25 million–6 billion per run) vary from platform to platform. Illumina application is well known in small- and big-size genomic sequencing and resequencing projects, transcriptome, SNP detection, and metagenomic studies ([http://](http://www.illumina.com/technology/next-generation-sequencing/sequencing-technology.html) [www.illumina.com/technology/next-generation-sequencing/sequencing-technol](http://www.illumina.com/technology/next-generation-sequencing/sequencing-technology.html)[ogy.html](http://www.illumina.com/technology/next-generation-sequencing/sequencing-technology.html)). Evolution in sequencing techniques is continued for next-generation sequencers due to high demand for a low-cost technology. Many sequencers are already in active practices from the third generation sequencer. Ion PGM (Personal Genome Machine) and ion proton are semiconductor-based sequencing platforms with automated workflow from sample preparation to analysis and having chipbased wide range of sequencing potentials, i.e., Ion 314™ Chip v2, Ion 316™ Chip v2, and Ion 318™ Chip v2 (read length, 200–400 bp; reads/run, 500 K–5 million). These sequencers are well used in targeted, small-scale studies and routine practices [\(https://www.thermofisher.com](https://www.thermofisher.com)/). PacBio RS is gaining popularity due to high long read lengths through single molecule real-time (SMRT) sequencing technology. It produces reads from 1 to 60 Kb. Each SMRT (single molecule real-time sequencing) cell can generate approximately 50,000 reads. PacBio RS is ideal for the sequencing of small genomes, regions of high G/C content, and DNA methylation, resequencing projects due to longer read length feature [\(http://www.pacb.com/prod](http://www.pacb.com/products-and-services/pacbio-systems/rsii/)[ucts-and-services/pacbio-systems/rsii/](http://www.pacb.com/products-and-services/pacbio-systems/rsii/)). Oxford nano-pore, based on nano-pore conductivity, is under active development. Current sequencing technologies offered several common benefits which are perfect for exploitative studies, i.e., no need of prior molecular information, molecular level sequence resolution, discovery of novel and rare transcripts, broad dynamic range, etc. But it imposed common technical problems as well, such as short read assembly and mapping, low coverage for GC content enriched region, sequencing error, etc. High coverage and deep sequencing can overcome these problems up to certain extent (Hui [2012](#page-25-5)).

### *2.3 Proteomics*

Proteomics is known for the study of quantitative measurement of proteins expressed by genome to characterize organism or biological processes which explain the mechanism of gene expression control. Field of protein research is continuously evolving since the isolation of individual proteins of *E. coli* from protein complexes through two-dimensional polyacrylamide gel electrophoresis (2-DE). Later, mass spectrometry (MS) was coupled with 2-DE gels for the identification of large

number of proteins which evolved as proteomics (Anderson and Anderson [1998\)](#page-24-6). Proteomics studies have three main components, i.e., expression proteomics, bioinformatics analysis, and functional proteomics. Expression proteomics is about sample preparation through gel-based or gel-free methods and protein identification analysis. Protein extraction methods can be different from protein to protein due to different physical and chemical properties of proteins. After protein extraction, 2-DE or liquid chromatography (LC) is used to isolate individual proteins from sample mixtures, and later these proteins are identified through MS-based methods. Quantitative proteomics have been used to identify proteins expressed in a specific cell or tissue, comparison of protein expression profile in differential experimental conditions or disease states to explore physiology and pathogenic mechanisms. Due to recent advancement, bioinformatics is extending its outreach to guide the future direction of functional proteomics studies. Bioinformatics analysis has been used in quantitative proteomics after the protein identification to gather different kinds of information, such as sequence alignment and homology; motifs and domains; transmembrane regions; protein structure, i.e., primary, secondary, tertiary, and quaternary; protein interactions and networks; as well as subcellular locations (Bencharit et al. [2013](#page-24-7)). Functional proteomics is a protein characterization approach of proteomics to understand the role of targeted proteins in cellular functions which requires high-throughput comprehensive analyses of protein-protein interactions, protein complexes, and transmembrane of organism. Bait- and prey-based approaches are very popular in functional proteomics like protein chip, coimmunoprecipitation techniques coupled with 2-DE, affinity chromatography, biomolecular interaction analysis mass spectrometry (BIA-MS), etc. (Chandramouli and Qian [2009\)](#page-24-8).

## *2.4 Metabolomics*

Metabolome is the collection of all kinds of metabolites in a biological cell, tissue, organ, or organism as the end products of cellular processes. Metabolomics profiling is getting popularity due to instant snapshot of the cell physiology, whereas gene expression and proteomics analyses are limited up to genes and their products being produced in the cell. Nowadays, metabolomics is integrated into "-omics" family along with genomics, proteomics, and transcriptomics to provide a better understanding of cellular biology (Johnson et al. [2014](#page-25-6)). Cellular metabolomics is a cohesive network of metabolite and biochemical interactions which have not yet been fully characterized for products, reactants, intermediate steps, and regulatory molecules. Metabolite profiling and metabolic fingerprinting are the major approaches used in metabolomics. Metabolite profiling is used to identify and quantify metabolites of plant cell. Metabolic fingerprinting is the high-throughput approach of metabolomics which is used for tissue comparison and discrimination analysis. Metabolomics is also used on the metabolic response of organisms to physiological stimuli or genetic modification (Johnson et al. [2014\)](#page-25-6).

### **3 Data Analysis**

#### *3.1 Gene Identification and Expression Analysis*

In both microarrays and NGS methods, we need to identify the expressed genes for further downstream analysis. There are several methods and tools already available for microarray based identification of expressed gene. This technology allows widespread changes in expression patterns to be probed in a single experiment. Gene expression is normalized in reference to control genes on a chip. Further, t-test and false discovery rate are applied to detect differentially expressed genes between treatment and control groups (Yadav et al. [2016](#page-26-1)).

Statistical analysis is an essential component for RNA-seq data, but due to the short history of the technology and its continuous development, there are no standard methods available yet to detect and analyze differentially expressed genes based on NGS data. Analytical programs for these data are just emerging and need to be evaluated. There are freely available R software packages which provide method to detect differentially expressed genes. Kvam et al. ([2012\)](#page-25-7) describe four recently proposed statistical methods (edgeR, DESeq, baySeq, and a method with two-stage Poisson model [TSPM]) on significance ranking of genes and false discovery rate control through simulation studies under various settings mimicking real data. Cufflinks tool has been developed to estimate transcript-level expression by tackling the problem of related transcripts' sharing most of their reads (Trapnell et al. [2010](#page-26-4)) and TopHat software (Li and Dewey [2011\)](#page-25-8) used for the estimates transcript abundances. The results show that the performances of different methods vary and that baySeq performs best in terms of significance ranking of genes. The false discovery rate may not be controlled well in practice, and they suggest applying a relatively stringent level to avoid too many false positives. In addition, the flexibility of handling different experimental design varies among the current versions of the different packages. Plant biologists may want to choose the one that best fits their experimental design and goal.

### *3.2 Gene Enrichment Functional Analysis*

To understand the biological context of DE (differentially expressed) genes, pathway enrichment analysis ensues. Once if the list of DE genes is available then we can start gaining biological insights into experimental systems, developmental stages, or understanding of disease or molecular mechanisms. In gene enrichment analysis experiments, gene transforms information from gene expression profiling into a pathway summary (Subramanian et al. [2005](#page-26-5)). Gene function enrichment analyses depend upon various annotation databases, for instance, Kyoto Encyclopedia of Genes and Genomes (KEGG) pathways (Kanehisa and Goto [2000](#page-25-9)), Gene Ontology (GO) (Botstein et al. [2000](#page-24-9)), DAVID (Huang et al. [2009\)](#page-25-10), etc. One traditional analysis starts with a gene list of interest, identified from differential RNA-seq or microarray analyses, and applies statistical methods, such as the Fisher's exact test to test for enrichment of each annotated gene set, network, and pathway. DE genes are quite often involved in the same biological pathways, and GSE (Gene Set Enrichment) results offer greater biological interpretability over individual gene analysis. GSVA (Gene Set Variation Analysis) (Hänzelmann et al. [2013](#page-25-11)) extends the current GSE methods to RNA-seq data, and provides increased power to detect subtle pathway activity changes, and constitutes a starting point to build pathway-centric models of systems biology. SeqGSEA (Wang and Cairns [2014\)](#page-26-6) is a new open-source Bioconductor package for GSVA, which can detect more biologically meaningful gene sets without biases toward longer and highly expressed genes. Previous pathway analysis methods have been developed based on algorithms considering pathways as simple gene lists and ignoring pathway structures. Recently, few methods have been developed to incorporate various aspects of pathway topology. For example, Yadav et al. [\(2016](#page-26-1)) have done the experiment to analyze the abiotic stress data in plants. Functional annotations were retrieved from the MapMan that is structured in the form of a hierarchical tree and was specifically designed to cover plant-specific pathways and processes. *Arabidopsis* genes were assigned into functional categories within the hierarchy of MapMan pathway scheme (Thimm et al. [2004](#page-26-7)). Pathway enrichment in each experiment was determined by calculating the cumulative hypergeometric *p* value for the probability that a group of genes are overrepresented within a functional bin at a rate higher than chance expectation.

### *3.3 Biological Network Topology and Characteristics*

Nodes and edges are the basic element for network building. In biological science, genes and proteins works as nodes, and functional or physical relationships between them are known as edges. In general, network topologies are defined as the order of nodes and edges to determine the functional aspects of the network. Node degree (i.e., number of edges connected to a node) and degree distribution (i.e., overall distribution of node degrees in a network) determine the nature of networks. The degree distribution of networks is often used to differentiate different classes of networks, whereas a number of edges are used to measure distances between networks. Navigability of network is measured through minimum path length (minimum number of edges) or mean path length (average of shortest path between all pairs of nodes). Node centrality or hub node is measured through the shortest path between all pairs of nodes in a network. In contrast to hub node, bottleneck node which does not necessarily have higher interaction works as linker between different subnetworks. A node can work as hub and bottleneck node both. Network robustness can also be characterized through network redundancy and degeneracy. Nodes' redundant connectivity through multiple paths is important for network sustainability and integrity in the absence of other connections, whereas network degeneracy is a special type of redundancy which leads to both overlapping and separate effects of network.

Network models are very important for the understanding of complex networks and explanation of observed network characteristics. Here, we described some basic models which are necessary for critical understanding of biological networks. Random network model assumes that all nodes are connected to approximately the same number of links, i.e., average and node degrees follow a Poisson distribution which indicates that nodes that significantly deviate from the average are extremely rare. Scale-free networks are well known to follow power-law degree distribution. It assumes that probability of highly connected node is statistically more significant than in a random graph. Network hub properties are determined by a relatively small number of highly connected nodes. Most of biological networks are very close to scale-free network. A substructure of large network is formed through densely connected node, and long-distance connection with other nodes is known as module or subnetwork. These modules are specialized for particular function like co-expression network where most of the nodes are organized in modules having limited connections between subparts of the network (Hu et al. [2016\)](#page-25-12). Network module graphically represents integrative genomics strategies used in current research that successfully identify candidate genes taking advantage of gene coexpression networks.

### **4 Networking Analysis**

# *4.1 Networking and Data Integration for System Level Understanding*

Gene set enrichment analysis provides information about all the genes which are significantly involved in cellular or metabolic pathway level processes at a given condition and time point. This plasticity generally involves changes at the level of DNA, RNA, protein, and metabolites, resulting in complex phenotypes governed by multiple genes. The major challenges in plant systems biology are to elucidate the genotype-phenotype relationship in plant cellular systems. The integrated network analysis tries to find correlation between genes and pathways which with the help of mathematical models have received particular attention.

### *4.2 Scale Within Network System*

One of the most key characteristic of system is the set of interactions existing between its constitutive elements. To understand complex interactions, the behavior of system needs to be modeled because it cannot be understood by direct approaches. Network approach is one of the common ways to model systems as a collection of its interacting elements. All the constitutive items of the system are represented as

set of nodes that are linked by edges which indicate the interactions between those items by means of mathematics. To represent systems as a unified whole into given network, all the nodes must be linked to other node by at least one edge; the mode of such linkage is called topology of the network (McCormack et al. [2016\)](#page-25-13). There are three main steps for modeling of a biological system: (1) We have to define which component will be considered as a node in the network and associate variables of interest and evolution rules to those nodes based on properties of the considered biological components. (2) Describe the association between the components of the system as edges associated with interaction functions in the system network. (3) Study the nature of the system under different conditions, changing evolution rules and network topology as dictated by experiment until a perfect prediction of the modeled system behavior can be achieved (Hu et al. [2016](#page-25-12)).

### *4.3 Analysis of Network*

There are two methods used to interpret the complexity of biology: one is "topdown" and another is "bottom-up" approach. In "top-down" method, large-scale datasets are analyzed to decode relationships between different levels of transcripts and proteins. On the other hand in "bottom-up" approach, properties of genes or proteins with available quantitative information such as kinetics data and transcription rates are used to construct a model of well-characterized components that can be simulated computationally to identify and predict the behavior of system in different conditions (Bassel et al. [2012\)](#page-24-10).

Approaches have been developed to identify functional modules in the plant science such as metabolic and regulatory modules. In the network system, characterization and recognition of the community structure is one of the major issues. At present time one highly effective method is the optimization of the quality function known as "modularity" over the possible divisions of a network. It can be expressed in terms of the eigenvectors of a characteristic matrix for the network which leads to a spectral algorithm for community detection (Zhao [2016\)](#page-26-8).

Co-expression of gene network method uses statistical matrices to create correlations between gene expression profiles for various samples on the basis of guilt-by-association rule (Bhardwaj and Lu [2005](#page-24-11)). The generation of co-expression networks is a feasible top-down approach to generate genome-wide cofunctional network models in plants. The Pearson correlation coefficient is generally used in co-expression networks to create linear pairwise correlations between enriched gene pairs in an adjacent matrix. For nonlinear correlations, another associative matrix that can be used is the Spearman correlation coefficient which enables nonlinear correlations between genes to be uncovered. A modified graphical Gaussian model that takes into account partial correlations between genes after removing the effects of other adjacent genes has also been used (Ma et al. [2007](#page-25-14)). Following the establishment of gene associations, a cutoff threshold is then set, and pairwise interaction values exceeding this selected threshold are kept. The strength of the correlations between gene pairs can be considered as edge

weights indicating the strength of co-regulation between gene pairs. The end result of such an approach is a network consisting of nodes which represent genes connected by edges showing significant similarity in their common expression pattern. It is important to note that both positively and negatively acting components of a biological process can be co-expressed (Lee et al. [2011\)](#page-25-15). Network analysis seeks to map and understand as systems-level views of cell behavior. In the context of gene, protein, and metabolites interactions, network biology provides the tools to answer questions such as the survival of plant during different abiotic stress (Yadav et al. [2016\)](#page-26-1), the effects of diverse environmental conditions on the flow of biological information between genes and proteins, and the phenotypic results of perturbations of protein communities.

### *4.4 Software and Tools for Network Analysis*

Researchers develop and use bioinformatics software or databases for the comprehensive study of plant systems biology. Many of the tools, databases, and other resources used in the analyses of the individual -omics platforms include the tools for network visualization, modeling environments, pathway construction and visualization tools, systems biology platforms, and repositories of the models. Visualization is a means of investigative data analysis and a key method for network analysis. The purpose of large -omics data visualization should be to create clear, meaningful, and integrated resources without being besieged by the inherent complexity of data (Gehlenborg et al. [2010](#page-25-16)). Pathway databases are used for modeling systems, since they offer a clear-cut way of building network topologies by the annotated reaction system. We have listed some of the widely used tools and databases by plant research community in Table [1](#page-11-0).

### **5 Application of Network System in Plant Biology**

### *5.1 Gene-to-Metabolite Network*

This network calculates the correlation and significance between differentially expressed genes which are associated with metabolic regulation at a given set of condition. In this interaction network, genes and metabolites act as node and edge, respectively. The interactions are interpreted depending on the distance between the genes and the metabolites. This type of network is highly complex and difficult to study in plants, owing to the enormous diversity and number of metabolites being produced in the cells due to their sessile lifestyle. In the area of plant science, geneto-metabolite networks elucidate the interrelations among biological processes, gene functional annotation, discovery of new genes in biosynthesis regulation, and transport of metabolites (Yuan et al. [2008](#page-26-9)). For the various biotic and abiotic stresses in plants, researchers utilize gene-to-metabolite networks to reveal how genes



<span id="page-11-0"></span>Table 1 Systems biology tools and database resources. Protein-protein interaction (1-24), metabolic pathways (25-35), signaling pathways (36-39), **Table 1** Systems biology tools and database resources. Protein-protein interaction  $(1-24)$ , metabolic pathways  $(25-35)$ , signaling pathways  $(36-39)$ , transcription factors/gene regulatory networks  $(40-48)$ , and genet





Table 1 (continued) **Table 1** (continued)





Table 1 (continued) **Table 1** (continued)



123



Table 1 (continued) **Table 1** (continued)





**Table 1** (continued)



regulate cellular pathways as well as primary and secondary metabolites synthesis to protect plants (Zulak et al. [2007](#page-26-10); Yadav et al. [2016\)](#page-26-1). These networks have helped in the discovery of novel candidate genes for terpenoid indole alkaloid biosynthesis in *Catharanthus roseus* (Rischer et al. [2006\)](#page-26-11) in response to nitrogen deficiency and during diurnal cycles (Blasing et al. [2005\)](#page-24-12) and so on.

### *5.2 Protein: Protein Interaction Network*

Protein-protein interactions (PPIs) are one of the most significant components of biological networks. In PPI networks, the nodes are proteins which are associated by direct edges if the direction of information flow during their interaction is known or nondirect edges if there is strong evidence of their physical interaction or association without an evidence for directionality of interaction (Assmann and Albert [2009\)](#page-24-13). Two types of interactions might be possible: genetic or physical. In genetic approaches, a network of genes characterized on the basis of genetic interactions to explain gene function within physiological processes (Boone et al. [2007\)](#page-24-14). Still, this method is difficult to implement owing to the ploidy levels and perennial plants. While in physical methods, interaction maps have been experimentally elucidated for homo- and hetero-dimerization within two large classes of transcription factors, for example, networks between the MADS box transcription factors (Immink et al. [2003;](#page-25-17) de Folter et al. [2005](#page-24-15)) and the MYB transcription factor family (Zimmermann et al. [2004a](#page-26-12), [b\)](#page-26-13).

#### *5.3 Carbohydrate: Protein Interaction Network*

People are exploring protein-carbohydrate interactions because it plays significant role in numerous physiological and pathological processes in plants. Recently, many computational methods have been suggested to study protein-carbohydrate interactions. Malik et al. (2014) developed a method to group various plant lectins and their interacting carbohydrates by the community detection analysis of a lectinglycan network generated by the glycan microarray data. They identified three lectins having large degrees of connectivity playing the roles of hubs. This work reveals global organization of lectin-glycan interactions and helps to identify strongly correlated lectin and glycan clusters in plants.

### *5.4 Transcriptional Regulatory Network*

Transcription regulatory network elucidates the regulatory interactions between transcription factors and downstream genes. To understand cellular dynamics, thorough knowledge of each regulatory network is required. In this network, nodes represent

transcription factors and regulatory genes, whereas edges represent transcriptional regulation (Babu et al. [2004\)](#page-24-16). There are various methods that are applied to interpret the transcriptional regulatory networks which includes genome-wide expression profiling and RNA interference (RNAi) screens (Baum and Craig [2004\)](#page-24-17). Nachman et al. presented transcription rate assessment by measurement of mRNA decay rates (Nachman et al. [2004](#page-25-18)). Other regulatory network models are evaluated based on promoter co-occupancy by pairs of transcription factors (Geisberg and Struhl [2004](#page-25-19)) and computational prediction of *cis*-elements (Beer and Tavazoie. [2004](#page-24-18)). In *Arabidopsis*, a transcriptional regulatory map was created for cold signaling mediated by the ICE1 transcription factor (Benedict et al. [2006](#page-24-19)), in rice to understand the role of oxidative signals in cold stress (Yun et al. [2010](#page-26-14); Todaka et al. [2012\)](#page-26-15), and in response to abiotic stresses in grasses (Nakashima et al. [2009\)](#page-25-20).

### *5.5 Gene Regulatory Network*

A gene regulatory network reveals role of genes in physiological processes of life, including cell differentiation, metabolism, the cell cycle, and signal transduction. In this network, the nodes correspond to genes and messengers RNAs or proteins, and the edges represent the regulatory interactions like activation, inhibition, and repression between the components of the network. Generally it's a collective network of genes, noncoding RNAs, proteins, metabolites, and signaling components (Long et al. [2008\)](#page-25-21). Gene regulatory network incorporates regulation of DNA transcription, RNA translation, posttranscriptional RNA processing, as well as the posttranslational modifications like protein targeting and covalent protein modifications. Gene regulatory networks display the dynamics of the plant systems (Yuan et al. [2008](#page-26-9)). Coen and Meyerowitz presented ABC model, a first plant gene regulatory networks model, and explained the interactions among transcription factors that regulate floral pattern formation across plant species (Coen and Meyerowitz [1991](#page-24-20)). The gene regulatory model controls guard cell size in stomatal closure (Li et al. [2006](#page-25-22)) in plants, and cell fate determination during flower development in *A. thaliana* (Espinosa-Soto et al. [2004](#page-25-23)). Reconstruction of biological network and analyses has been an important method in plant systems biology. Figure [2](#page-23-0) graphically illustrates the central part of typical systems biology method which is thoroughly discussed in this chapter.

#### **6 Conclusion and Future Prospective**

It is a scientific challenge to incorporate every piece of biological knowledge into a unified manner, but there is a requirement of an iterative process between different experimental data and mathematical modeling. In the last few years, systems

<span id="page-23-0"></span>

**Fig. 2** Graphical representation of systems biology approach in plant biology

biology approach is employed to address key biological questions which provide crucial information and developed hypothesis not only in plant but also in the other areas of life sciences. This chapter defines how to accomplish our research; it starts with genomics and makes relationships between gene-gene, gene to protein, protein-protein, and gene to metabolites. To make this correlation, various methods calculate confidence hypothesis between entities which adds depth breadth to a network and leads to the identification of general network properties. Validation of generated biological network by the various screens and predictions, and their functional consequences in a spatiotemporal manner, is still major challenge. For example, protein-protein interaction shades were attained in systems that do not deliver the spatiotemporal environment of complex formation in addition with protein levels exceeding the native levels. To understand these networks, information is required at the cellular, tissue, and whole-plant system levels. The interpretation of biological networks is important to link an organism that can develop, grow, and reproduce. There are some studies which have nicely demonstrated gene regulation in developmental processes and functions of the cell type and tissue, to understand transcriptional dynamics using cell- and tissue-specific transcript profiling. In system and network biology to understand regulatory networks and protein-protein interactions, it will be important to implement structural features and posttranslational modifications.

# **References**

- <span id="page-24-6"></span>Anderson NL, Anderson NG (1998) Proteome and proteomics: new technologies, new concepts, and new words. Electrophoresis 19(11):1853–1861
- <span id="page-24-13"></span>Assmann SM, Albert R (2009) Discrete dynamic modeling with asynchronous update, or how to model complex systems in the absence of quantitative information. Plant Syst Biol 553:207–225
- <span id="page-24-16"></span>Babu MM, Luscombe NM, Aravind L, Gerstein M, Teichmann SA (2004) Structure and evolution of transcriptional regulatory networks. Curr Opin Struct Biol 14(3):283–291
- <span id="page-24-10"></span>Bassel GW, Gaudinier A, Brady SM, Hennig L, Rhee SY, De Smet I (2012) Systems analysis of plant functional, transcriptional, physical interaction, and metabolic networks. Plant Cell 24(10):3859–3875
- <span id="page-24-17"></span>Baum B, Craig G (2004) RNAi in a postmodern, postgenomic era. Oncogene 23(51):8336–8339
- <span id="page-24-18"></span>Beer MA, Tavazoie S (2004) Predicting gene expression from sequence. Cell 117(2):185–198
- <span id="page-24-7"></span>Bencharit S, Border MB, Edelmann A, Byrd WC (2013) Update in research and methods in proteomics and bioinformatics. Expert Rev Proteomics 10(5):413–415
- <span id="page-24-19"></span>Benedict C, Geisler M, Trygg J, Huner N, Hurry V (2006) Consensus by democracy. Using metaanalyses of microarray and genomic data to model the cold acclimation signaling pathway in Arabidopsis. Plant Physiol 141(4):1219–1232
- <span id="page-24-11"></span>Bhardwaj N, Lu H (2005) Correlation between gene expression profiles and protein–protein interactions within and across genomes. Bioinformatics 21(11):2730–2738
- <span id="page-24-0"></span>Bi YM, Kant S, Clark J, Gidda S, Ming F, Xu J, Rochon A, Shelp BJ, Hao L, Zhao R, Mullen RT (2009) Increased nitrogen-use efficiency in transgenic rice plants over-expressing a nitrogenresponsive early nodulin gene identified from rice expression profiling. Plant Cell Environ 32(12):1749–1760
- <span id="page-24-12"></span>Bläsing OE, Gibon Y, Günther M, Höhne M, Morcuende R, Osuna D, Thimm O, Usadel B, Scheible WR, Stitt M (2005) Sugars and circadian regulation make major contributions to the global regulation of diurnal gene expression in *Arabidopsis*. Plant Cell 17(12):3257–3281
- <span id="page-24-14"></span>Boone C, Bussey H, Andrews BJ (2007) Exploring genetic interactions and networks with yeast. Nat Rev Genet 8(6):437–449
- <span id="page-24-9"></span>Botstein D, Cherry JM, Ashburner M, Ball CA, Blake JA, Butler H, Davis AP, Dolinski K, Dwight SS, Eppig JT (2000) Gene ontology: tool for the unification of biology. Nat Genet 25(1):25–29
- <span id="page-24-1"></span>Bräutigam A, Schliesky S, Külahoglu C, Osborne CP, Weber AP (2014) Towards an integrative model of C4 photosynthetic subtypes: insights from comparative transcriptome analysis of NAD-ME, NADP-ME, and PEP-CK C4 species. J Exp Bot 65(13):3579–3593
- <span id="page-24-4"></span>Bumgarner R (2013) Overview of DNA microarrays: types, applications, and their future. Curr Protoc Mol Biol Chapter 22:Unit 22.1
- <span id="page-24-2"></span>Carstens M, McCrindle TK, Adams N, Diener A, Guzha DT, Murray SL, Parker JE, Denby KJ, Ingle RA (2014) Increased resistance to biotrophic pathogens in the Arabidopsis constitutive induced resistance 1 mutant is EDS1 and PAD4-dependent and modulated by environmental temperature. PLoS One 9(10):e109853
- <span id="page-24-8"></span>Chandramouli K, Qian PY (2009) Proteomics: challenges, techniques and possibilities to overcome biological sample complexity. Hum Genom Prot 2009:1–22
- <span id="page-24-5"></span>Chen WJ, Zhu T (2004) Networks of transcription factors with roles in environmental stress response. Trends Plant Sci 9(12):591–596
- <span id="page-24-3"></span>Chinchilla D, Zipfel C, Robatzek S, Kemmerling B, Nürnberger T, Jones JD, Felix G, Boller T (2007) A flagellin-induced complex of the receptor FLS2 and BAK1 initiates plant defence. Nature 448(7152):497
- <span id="page-24-20"></span>Coen ES, Meyerowitz EM (1991) The war of the whorls: genetic interactions controlling flower development. Nature 353(6339):31–37
- <span id="page-24-15"></span>De Folter S, Immink RG, Kieffer M, Pařenicová L, Henz SR, Weigel D, Busscher M, Kooiker M, Colombo L, Kater MM, Davies B (2005) Comprehensive interaction map of the *Arabidopsis* MADS box transcription factors. Plant Cell 17(5):1424–1433
- <span id="page-25-23"></span>Espinosa-Soto C, Padilla-Longoria P, Alvarez-Buylla ER (2004) A gene regulatory network model for cell-fate determination during *Arabidopsis thaliana* flower development that is robust and recovers experimental gene expression profiles. Plant Cell 16(11):2923–2939
- <span id="page-25-16"></span>Gehlenborg N, O'Donoghue SI, Baliga NS, Goesmann A, Hibbs MA, Kitano H, Kohlbacher O, Neuweger H, Schneider R, Tenenbaum D, Gavin AC (2010) Visualization of omics data for systems biology. Nat Methods 7:S56–S68
- <span id="page-25-19"></span>Geisberg JV, Struhl K (2004) Quantitative sequential chromatin immunoprecipitation, a method for analyzing co-occupancy of proteins at genomic regions in vivo. Nucleic Acids Res 32(19):e151
- <span id="page-25-11"></span>Hänzelmann S, Castelo R, Guinney J (2013) GSVA: gene set variation analysis for microarray and RNA-seq data. BMC Bioinforma 14(1):7
- <span id="page-25-3"></span>Hirschhorn JN, Sklar P, Lindblad-Toh K, Lim YM, Ruiz-Gutierrez M, Bolk S, Langhorst B, Schaffner S, Winchester E, Lander ES (2000) SBE-TAGS: an array-based method for efficient single-nucleotide polymorphism genotyping. Proc Natl Acad Sci 97(22):12164–12169
- <span id="page-25-12"></span>Hu JX, Thomas CE, Brunak S (2016) Network biology concepts in complex disease comorbidities. Nat Rev Genet 17:615–629
- <span id="page-25-10"></span>Huang DW, Sherman BT, Lempicki RA (2009) Systematic and integrative analysis of large gene lists using DAVID bioinformatics resources. Nat Protoc 4(1):44–57
- <span id="page-25-5"></span>Hui P (2012) Next generation sequencing: chemistry, technology and applications. In: Chemical diagnostics. Springer, Berlin, pp 1–18
- <span id="page-25-17"></span>Immink RG, Ferrario S, Busscher-Lange J, Kooiker M, Busscher M, Angenent GC (2003) Analysis of the petunia MADS-box transcription factor family. Mol Gen Genomics 268(5):598–606
- <span id="page-25-6"></span>Johnson CH, Ivanisevic J, Benton HP, Siuzdak G (2014) Bioinformatics: the next frontier of metabolomics. Anal Chem 87(1):147–156
- <span id="page-25-9"></span>Kanehisa M, Goto S (2000) KEGG: kyoto encyclopedia of genes and genomes. Nucleic Acids Res 28(1):27–30
- <span id="page-25-0"></span>Kanwal S, Ashraf M, Shahbaz M, Iqbal MY (2013) Influence of saline stress on growth, gas exchange, mineral nutrients and non-enzymatic antioxidants in mungbean [(Vigna radiata (L.) Wilczek]. Pak J Bot 45(3):763–771
- <span id="page-25-7"></span>Kvam VM, Liu P, Si Y (2012) A comparison of statistical methods for detecting differentially expressed genes from RNA-seq data. Am J Bot 99(2):248–256
- <span id="page-25-15"></span>Lee I, Blom UM, Wang PI, Shim JE, Marcotte EM (2011) Prioritizing candidate disease genes by network-based boosting of genome-wide association data. Genome Res 21(7):1109–1121
- <span id="page-25-1"></span>Leal WS (2013) Odorant reception in insects: roles of receptors, binding proteins, and degrading enzymes. Annu Rev Entomol 58(1):373–391
- <span id="page-25-8"></span>Li B, Dewey CN (2011) RSEM: accurate transcript quantification from RNA-Seq data with or without a reference genome. BMC Bioinforma 12:323
- <span id="page-25-22"></span>Li S, Assmann SM, Albert R (2006) Predicting essential components of signal transduction networks: a dynamic model of guard cell abscisic acid signaling. PLoS Biol 4(10):e312
- <span id="page-25-21"></span>Long TA, Brady SM, Benfey PN (2008) Systems approaches to identifying gene regulatory networks in plants. Annu Rev Cell Dev Biol 24:81
- <span id="page-25-14"></span>Ma S, Gong Q, Bohnert HJ (2007) An *Arabidopsis* gene network based on the graphical Gaussian model. Genome Res 17(11):1614–1625
- Malik A, Lee J, Lee J (2014) Community-based network study of protein-carbohydrate interactions in plant lectins using glycan array data. PLoS One 9(4):e95480
- <span id="page-25-13"></span>McCormack ME, Lopez JA, Crocker TH, Shahid Mukhtar M (2016) Making the right connections: network biology and plant immune system dynamics. Curr Plant Biol 5:2–12
- <span id="page-25-4"></span>Metzker ML (2010) Sequencing technologies—the next generation. Nat Rev Genet 11(1):31–46
- <span id="page-25-2"></span>Mishra A, Pandey D, Singh M, Kumar A (2011) Involvement of hsr203J like gene homologue, protease and protease inhibitors in triggering differential defense response against Alternaria blight in Brassica. Australas Plant Pathol 40(5):461
- <span id="page-25-18"></span>Nachman I, Regev A, Friedman N (2004) Inferring quantitative models of regulatory networks from expression data. Bioinformatics 20(suppl 1):i248–i256
- <span id="page-25-20"></span>Nakashima K, Ito Y, Yamaguchi-Shinozaki K (2009) Transcriptional regulatory networks in response to abiotic stresses in *Arabidopsis* and grasses. Plant Physiol 149(1):88–95
- <span id="page-26-11"></span>Rischer H, Orešič M, Seppänen-Laakso T, Katajamaa M, Lammertyn F, Ardiles-Diaz W, Van Montagu MC, Inzé D, Oksman-Caldentey KM, Goossens A (2006) Gene-to-metabolite networks for terpenoid indole alkaloid biosynthesis in Catharanthus roseus cells. Proc Natl Acad Sci 103(14):5614–5619
- <span id="page-26-0"></span>Sheth BP, Thaker VS (2014) Plant systems biology: insights, advances and challenges. Planta 240(1):33–54
- <span id="page-26-2"></span>Sreenivasulu N, Wobus U (2013) Seed-development programs: a systems biology–based comparison between dicots and monocots. Annu Rev Plant Biol 64:189–217
- <span id="page-26-5"></span>Subramanian A, Tamayo P, Mootha VK, Mukherjee S, Ebert BL, Gillette MA, Paulovich A, Pomeroy SL, Golub TR, Lander ES, Mesirov JP (2005) Gene set enrichment analysis: a knowledge-based approach for interpreting genome-wide expression profiles. Proc Natl Acad Sci 102(43):15545–15550
- <span id="page-26-7"></span>Thimm O, Bläsing O, Gibon Y, Nagel A, Meyer S, Krüger P, Selbig J, Müller LA, Rhee SY, Stitt M (2004) Mapman: a user-driven tool to display genomics data sets onto diagrams of metabolic pathways and other biological processes. Plant J 37(6):914–939
- <span id="page-26-15"></span>Todaka D, Nakashima K, Shinozaki K, Yamaguchi-Shinozaki K (2012) Toward understanding transcriptional regulatory networks in abiotic stress responses and tolerance in rice. Rice 5(1):1
- <span id="page-26-4"></span>Trapnell C, Williams BA, Pertea G, Mortazavi A, Kwan G, van Baren MJ et al (2010) Transcript assembly and quantification by RNA-Seq reveals unannotated transcripts and isoform switching during cell differentiation. Nat Biotechnol 28:511–515
- <span id="page-26-6"></span>Wang X, Cairns MJ (2014) SeqGSEA: a Bioconductor package for gene set enrichment analysis of RNA-Seq data integrating differential expression and splicing. Bioinformatics 30:1777–1779. btu090
- <span id="page-26-1"></span>Yadav BS, Lahav T, Reuveni E, Chamovitz DA, Freilich S (2016) Multidimensional patterns of metabolic response in abiotic stress-induced growth of *Arabidopsis thaliana*. Plant Mol Biol 15:1–1
- <span id="page-26-3"></span>Yamaguchi-Shinozaki K, Shinozaki K (2005) Organization of cis-acting regulatory elements in osmotic-and cold-stress-responsive promoters. Trends Plant Sci 10(2):88–94
- <span id="page-26-9"></span>Yuan JS, Galbraith DW, Dai SY, Griffin P, Stewart CN (2008) Plant systems biology comes of age. Trends Plant Sci 13(4):165–171
- <span id="page-26-14"></span>Yun KY, Park MR, Mohanty B, Herath V, Xu F, Mauleon R, Wijaya E, Bajic VB, Bruskiewich R, de los Reyes BG (2010) Transcriptional regulatory network triggered by oxidative signals configures the early response mechanisms of japonica rice to chilling stress. BMC Plant Biol 10(1):1
- <span id="page-26-8"></span>Zhao G, Jiang K, Zhang T, Wu H, Qiu C, Deng G (2016) Specific interferon tau gene-regulation networks in bovine endometrial luminal epithelial cells. Theriogenology 105:51–60
- <span id="page-26-12"></span>Zimmermann IM, Heim MA, Weisshaar B, Uhrig JF (2004a) Comprehensive identification of *Arabidopsis thaliana* MYB transcription factors interacting with R/B-like BHLH proteins. Plant J 40(1):22–34
- <span id="page-26-13"></span>Zimmermann P, Hirsch-Hoffmann M, Hennig L, Gruissem W (2004b) GENEVESTIGATOR. *Arabidopsis* microarray database and analysis toolbox. Plant Physiol 136(1):2621–2632
- <span id="page-26-10"></span>Zulak KG, Cornish A, Daskalchuk TE, Deyholos MK, Goodenowe DB, Gordon PM, Klassen D, Pelcher LE, Sensen CW, Facchini PJ (2007) Gene transcript and metabolite profiling of elicitor-induced opium poppy cell cultures reveals the coordinate regulation of primary and secondary metabolism. Planta 225(5):1085–1106